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ABSTRACT

Title of dissertation: DO CELLMATES MATTER?
A STUDY OF PRISON PEER EFFECTS
UNDER ESSENTIAL HETEROGENEITY

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This study examines prison peer effects in an adult prison population in the United States using a unique dataset assembled from the administrative databases of the Pennsylvania Department of Corrections. The members of a first-time prison release cohort were identified and matched to each of the cellmates with whom they shared a double cell. These data were then linked to arrest history data from the Pennsylvania State Police.

Criminological theories of social influence expect unobserved and difficult to quantify factors, such as criminality, to affect criminal behavior both independently and through intermediate decisions, including the choice to maintain prison peer associations. Those theories, therefore, implicitly assume the presence of essential heterogeneity, which helps to account for the response heterogeneity observed in studies of social influence. This study introduces the concept of essential heterogeneity to criminology and is the first to apply a method to address it, local instrumental variables, to estimate causal social interaction effects.

The analyses presented in this study demonstrate that there is considerable response heterogeneity in prison peer effects. That response heterogeneity is attributable to essential heterogeneity, as implicitly expected by criminological learning theories. However, the null average effects estimated do not accord with the predictions of criminological learning theories, including differential association, balance, and prisonization theories, each of which expects peers who are, on average, more criminally experienced to exert criminogenic effects.

The presence of essential heterogeneity indicates that estimating average prison peer effects does little to adequately characterize the relationship between social interactions with cellmates and releasee reoffending behaviors. Within the null average prison peer effect estimates lies tremendous variation in marginal prison peer effects. Some marginal prison peer effects are significantly criminogenic, while others are significantly crimino-suppressive. That substantial variation in the measured effect of prison peers on reoffending persists despite rigorous analysis and the inclusion of robust theoretically relevant controls suggests that future work should focus on creating constructs more appropriate to the task of determining who is harmed and who is helped as a result of interactions with prison peers.

DO CELLMATES MATTER?
A STUDY OF PRISON PEER EFFECTS UNDER ESSENTIAL HETEROGENEITY

by

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DEDICATION

To all my BCFs out there, both literal and figurative: Thank you for helping me deal with the BFCs in my life. Among so many other things, I appreciate the fact that I don't have to spell things out for you.

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CHAPTER 1: Introduction

Why do average prison effects on reoffending appear null or criminogenic, as opposed to crimino-suppressive? To explain why incarceration fails to reduce reoffending, Nagin, Cullen, and Jonson (2009) have suggested that prisons have failed to exert specific deterrent effects on prisoners. What causes that failure remains unknown. Potential explanations include the stigma of the prison experience, defiant responses to harsh prison conditions, and criminogenic social influences. With respect to the latter, it has been suggested that social interactions amongst prisoners can increase their criminality and, thereby, encourage their reoffending (Bentham, 1830; Clemmer, 1940. 1950; Sutherland & Cressey, 1955; Nagin, et al., 2009; Nagin, 2013).

The Theory behind Prison Peer Effects

A plausible theoretical rationale for the presence of criminogenic prison peer effects invokes social influence through learning mechanisms. According to Sutherland's (1947) differential association theory, an individual's criminality or underlying tendency to engage in criminal behavior emerges and is exacerbated through interactions with other individuals who hold criminal values and have criminal skills that supplement their own. These behaviors are acquired through ordinary learning processes such as modeling, reinforcement, punishment, and dialogue (Sutherland, 1947; Skinner, 1953; Bandura, 1962; Burgess & Akers, 1966; Dishion & Dodge, 2005; Akers, 2009). The duration of association moderates the effects exerted through these processes, such that longer periods of time spent with in association with peers increase peer effects (Agnew, 1991; Warr, 1993). Via developmental cascade theory (Masten et al., 2005), peer influence operating through the aforementioned processes has also been theorized to affect outcomes for many years after the social interactions have occurred (Dishion, Veronneau, & Myers, 2010).

With respect to social interactions in prison, Clemmer (1940, 1950) argued that associating with other inmates leads to varying degrees of assimilation to the prison context (i.e., *prisonization*), a normative socialization process that exacerbates criminality. He expected the ordinary learning mechanisms that support normative socialization outside prison to operate inside prison as well (Sutherland, 1947; Clemmer, 1940, 1950; Gold & Osgood, 1992; Jones & Schmid, 2000).

Clemmer (1950) expected that prisonization would occur particularly through social interactions with cellmates. He predicted "a chance placement with a cellmate" (Clemmer, 1950, p. 317) to influence the development of prisonization, which proceeds primarily through that initial association. Gold and Osgood (1992) confirmed his prediction, finding that peer effects were most likely to arise between cellmates in the juvenile facilities they studied in Michigan.

Clemmer (1940) also predicted that the magnitude of prisonization effects would increase with time served, just as Sutherland (1947) predicted that peer effects would intensify over time. In contrast, Wheeler (1961) and his contemporaries found that the degree to which inmates become prisonized follows a parabolic curve such that the prisonization effects rise, peak, and later subside as inmates approached their release dates (Garabedian, 1963; Wellford, 1967). Wheeler (1961) further found that inmates who were returning to prison appear to be more prisonized than did the first-time inmates he examined.

To account for their findings, Wheeler (1961) and his contemporaries hypothesized that inmates interact with different reference groups (Merton, 1957) at different times during their prison stays, such that time served interacts with prison peer characteristics to yield prison peer effects (Glaser & Stratton, 1961), just as duration must interact with the characteristics of peers to yield peer effects (Sutherland, 1947). Thus, both the duration of association with a cellmate and the timing of that association relative to the inmate's prison stay are theorized to interact with the cellmate's criminality and criminal experience to foment reoffending.

Even among prison inmates, the characteristics of criminals vary (Clemmer, 1940, 1950). Criminogenic prison peer effects are theorized emanate from associations with inmates with more criminal experience or higher levels of criminality (Sutherland 1947, Clemmer, 1940, 1950; Nagin et al., 2009). However, prison peer effects can inhibit reoffending in released prisoners just as they can excite it. According to McGloin (2009), whether offending increases or decreases after peer interactions depends on the relative distance between the criminality and criminal experience of the interacting peers. Applying McGloin's (2009) balance theory to the prison context yields the expectation that prisoners in dyadic associations will moderate toward each other in terms of the criminal attitudes they adopt and the criminal behaviors in which they engage. Inmates with lesser criminality or criminal experience than their cellmates will experience criminogenic effects, whereas inmates in possession of more criminality and criminal experience than their cellmates will experience crimino-suppressive effects.

If social interactions with cellmates are to help to explain the average failure of incarceration to produce specific deterrent effects, they must exert criminogenic effects, on average, such that indications of increased criminal activity attributable to prison peer effects should be observed several years after inmates are released from prison. Specifically, after interacting with a relatively more criminal cellmate (i.e., an inmate who has, in the parlance of Sutherland, adopted more criminal definitions), an inmate's probability of reoffending should increase. To accord with the prison effect or incarceration and reoffending literature, the effects of those prison peer interactions with a cellmate then have the potential to influence reoffending outcomes measured at least three years post-release (Nagin et al., 2009; Dishion, 2014).

Prior Evidence of Criminogenic Prison Peer Effects

In the single published study that examined social interaction effects in an incarcerative environment, Bayer, Hjalmarsson, and Pozen (2009) found that delinquents housed in juvenile correctional facilities with other delinquents who had committed similar offenses were more likely to commit those offenses after their release. Another unpublished study tentatively confirms these findings among inmates housed in dormitory-style prisons in France (Ouss, 2011). Although this direct evidence of prison peer effects is sparse, it supports the notion that prison peer effects are criminogenic rather than crimino-suppressive and that they, therefore, can account for some portion of the hypothesized failure of specific deterrence.

Potential Prison Peer Effect Identification Issues

Identifying whether interactions between social actors produce measurable, causal peer effects is a notoriously difficult statistical estimation problem that requires consideration of endogenous selection into social associations, reciprocity in the outcomes proceeding from those associations, and contextual influences on those outcomes (Manski, 1993). In observational social interaction studies across disciplines, the simultaneous nature of social relationships has generally gone unaddressed, as have the selection biases and contextual effects that contaminate estimates of social interaction effects (Gottfredson & Hirschi, 1990; Manski, 1993, 2000; Mouw, 2006; Gangl, 2010; Angrist, 2013; Sacerdote, 2014). Thus, while an association between the behaviors of social actors is well established in the criminological literature (Warr, 2002; Pratt et al., 2010), a persistent problem is that those associations are often mistaken for causal effects (Gottfredson & Hirschi, 1990; Nichols, 2007). These deficiencies have allowed the criminological debate over whether social influence matters in the production of behavior, criminal or otherwise, to persist because deniers of social influence can convincingly argue that effects attributed to social influence are actually attributable to selection, simultaneity, or contextual biases (Gottfredson & Hirschi, 1990; Sampson & Laub, 2005; Matsueda, 1988; Costello & Vowell, 1999, McGloin & Shermer, 2009).

While the current study is unlikely to resolve that criminological debate, it both offers a novel perspective on the problem of social interaction effect identification and employs a more appropriate method to identify those effects. The analysis provides insight into the well-known reason why well-controlled studies of social interactions have generally produced only meager evidence of their effects (e.g., Osgood & Briddell, 2006; Angrist, 2013): average treatment effects estimated through regression techniques obscure important response heterogeneity (Nagin, 1999; Heckman, 2000; Heckman & Vytlacil, 2005; Loughran & Mulvey, 2010).

Response heterogeneity is endemic to criminological research. In the framework of the current study, response heterogeneity means that observationally equivalent inmates respond to observationally equivalent cellmates differently: some inmates might be harmed by prison peer interactions, while other inmates are helped by them. In the context of the measurement of peer effects, one reason analyses tend to display response heterogeneity is that not all of the factors crucial to the determination of outcomes are observed (i.e., there are omitted variables). In a prison peer context, this means that reoffending outcomes generated by maintaining cellmate associations are affected by factors about which researchers have little or no information. That this *unobserved heterogeneity* or *selection on levels* plays a role in outcomes is canonical (Heckman, 1976; Heckman & Singer, 1984; Wooldridge, 2006).

That selection on levels is only one source of potential bias emanating from the unobserved determinants of outcomes is less established (Manski, 2005; Heckman, Urzua, & Vytlacil, 2006). Importantly, cellmate associations might be maintained (by inmates or correctional officers) for reasons related to their potential to affect inmates' reoffending. Expectations regarding the reoffending outcomes of cellmate associations are also unobserved by the researcher (Manski, 2005; Heckman et al., 2006; Brave & Walstrum, 2014). The phenomenon whereby decisions are made based on the outcomes they are expected to yield is called *selection on gains*. Heckman, et al. (2006) call response heterogeneity that results from a combination of selection on levels and selection on gains *essential heterogeneity*.

Analytic techniques that eliminate biases due to selection on levels do not eliminate biases due to selection on gains (Heckman & Vytlacil, 2005; Heckman et al., 2006). This includes average effect estimates from instrumental variables techniques, which have been touted as a panacea for the measurement of social interaction effects

(Fletcher, 2009, 2012). The estimates generated through these analytic techniques either remain biased or apply only to a small portion of the sample under study.

The local instrumental variables method (Heckman & Vytlacil, 2005), described below, illuminates the potential harm can be caused when estimated treatment effects remain biased by essential heterogeneity. In the current context, if essential heterogeneity is present in the relationship between cellmate associations and reoffending outcomes arising from those associations, average prison peer effect estimates may have little meaning because they will not characterize the breadth of responses to those associations. More crucially, average prison peer effect estimates may misrepresent the impact of cellmate associations for many inmates. Polices based on those averages may harm many inmates.

Data

The current study was made possible through the creation of an original dataset assembled from administrative records maintained by the Pennsylvania Department of Corrections (PADOC) and the Pennsylvania State Police (PSP). A cohort of males admitted to PADOC custody for the first time on or after January 1, 2000 and released between January 1, 2006 and December 31, 2007 was selected. The inmates who shared double cells with those first-time releasees were identified. Record of Arrest and Prosecution (RAP) sheets for the releasees and their cellmates were then obtained from the PSP. Information from interviews, observations, and surveys of correctional officers supplement the administrative data.

Analytic Plan

To translate the data into an analytic framework best capable of estimating causal prison peer effects, several operationalizations were made. The first-time releasees have no prior prison experience that might contaminate socialization effects in prison (Wheeler, 1961; Nieuwbeerta, Nagin, & Blokland, 2009). The longest-duration cellmate associations maintained by the releasees enable examination of prison peer effects among the cellmate associations (Clemmer, 1940; Gold & Osgood, 1992) most likely to exert social interaction effects due to their time intensity (Sutherland, 1947; Warr, 1993).

Only behavioral indicators of criminality and criminal experience are available in the PADOC data. This is a minor limitation, as behavioral peer measures have been shown to be predictive of offending outcomes in both the differential association and balance theory frameworks (Warr & Stafford, 1991; McGloin, 2009; Pratt et al., 2010). The criminality and criminal experience (i.e., social interaction) measures include: an indicator of whether the longest-duration cellmate had a prior incarceration, a relative releasee-cellmate prior arrest measure, and a relative releasee-cellmate recidivism risk (i.e., criminality) measure that was constructed based on PADOC's Risk Screening Tool assessment. Reoffending is measured by rearrest and a more general recidivism measure, which is defined as criminal justice system involvement that includes both rearrest and reincarceration without rearrest (Maltz, 1984; Grattet, Petersilia, Lin, & Beckman, 2011; Grattet, Lin, & Petersilia, 2011).

The duration of cellmate association differentiates the dyadic pairs that have already been identified, as described above. Duration emerged as a potential differentiating characteristic because Sutherland (1947) argued that the duration of association moderates peer influence and because prior prisonization research had shown that the timing of the acceleration of prisonization, which cellmate associations are theorized to foment, varies over the course of a prison stay (Wheeler, 1961; Garabedian, 1963; Wellford, 1967). The timing of the most stable releasee-cellmate associations also indicates that the development of prisonization may be due to the fact that cellmate associations may take some time to develop before producing prison peer effects (Clemmer, 1940, 1950). Therefore, when during the course of a cellmate association prison peer effects are most likely to emerge must be determined.

The need to explore the evolution of prison peer relationships over time introduces a complication because the duration of cellmate association is measured as a continuous number of days, whereas celling decisions (i.e., whether to pair two inmates) are binary decision processes. To preserve the binary character of the celling decisions, *duration thresholds* (i.e., points at which the duration of cellmate association can be dichotomized) are chosen. Those duration thresholds ensure that the releasees who meet a particular duration threshold and the releasees who do not are comparable based on their observed information. Once the thresholds are chosen, the potential moderating effects of duration of association, as predicted by Sutherland (1947), are explored between them.

To estimate average causal prison peer effects proceeding from cellmate associations, the current study assumes a potential outcomes framework (Roy, 1951; Cox, 1958; Rubin, 1978; Angrist & Pischke, 2009) in which duration of cellmate association thresholds are treatment modalities that moderate social interactions, as measured by relative criminality and criminal experience, and the prevalence of reoffending is the outcome, as measured by rearrest and recidivism. In this framework, two processes sequentially determine releasee reoffending: a binary decision-making process (i.e., an inmate's decision to remain with his longest-duration cellmate) that determines whether two inmates maintain their association or not and the process of ongoing social interaction that emanates from that decision to produce reoffending.

These two processes require an analytic framework that includes two models to estimate prison peer effects. While common instrumental variables (IV) approaches, such as two-stage least squares, fit a two-stage potential outcomes framework and overcome the bias introduced by selection on levels (Heckman, 1976; Imbens & Angrist, 1994; Fletcher, 2009, 2012; Bushway & Apel, 2010), they do not address the essential heterogeneity that includes selection on gains (Heckman et al., 2006). To elicit causal treatment effects under essential heterogeneity, Heckman & Vytlacil's (1999, 2001, 2005) local instrumental variables (LIV) estimation strategy will be used to examine whether cellmates exert social influence that increases reoffending.

The local instrumental variables method extends the potential outcomes framework (Heckman & Vytlacil, 1999, 2005). As is the case in ordinary IV strategies, LIV employs exclusion restrictions to estimate a choice model, from which the probability that a cellmate association lasts for several months or longer can be predicted. This probability is referred to as the *propensity score*. The propensity score is a summary of an inmate's probability of opting into a cellmate association duration threshold based on the observable information. The propensity score is the main independent variable in the second-stage outcome model that predicts reoffending. After the second stage is estimated its derivative is then taken with respect to the propensity score to enable estimation of marginal prison peer effects on reoffending. This derivative is the local variable to which the name of the method refers (Heckman & Vytlacil, 1999, 2005; Heckman et al., 2006).

Marginal treatment effects are calculated by evaluating the derivative of the outcome model across the range of the propensity score and, in the current case, for average values of the covariates. Marginal treatment effects are expressed in terms of the propensity not to be treated so that the collective contribution that unobserved factors make to the outcomes can be quantified. Marginal prison peer effects are generated by varying the values of the social interaction variables (prior incarceration, prior arrest, recidivism risk) around those means. Integrating the marginal prison peer effects over the propensity score generates average prison peer effects.

Main Results

That average prison peer effect parameter can be a very misleading summary statistic. As is implicit in criminological learning theories, the analysis reveals the presence of essential heterogeneity, which leads to variation in reoffending outcomes as a function of the probability of celling with a cellmate for several months. Some releasees experience criminogenic prison peer effects, while others experience crimino-suppressive prison peer effects. Average prison peer effects are null.

While an average prison peer effect parameter may in many cases be a poor representation of the effect of an individual cellmate on his prison peer, it can be used to answer the question of whether average prison peer effects help to explain average prison effects. On average, social interactions between cellmates do not appear to increase or to decrease the prevalence of releasee reoffending, as measured by rearrest or recidivism. These null average prison peer effects cannot, therefore, account for average criminogenic prison effects. Moreover, the finding that cellmates who are more criminogenic, on average, than the releasees with whom they are paired do not increase reoffending in the release cohort, on average, contradicts the predictions made by criminological learning theories, including theories of differential association (Sutherland, 1947), balance (McGloin, 2009), and prisonization (Clemmer, 1940).

Main Contributions

The current study makes both conceptual and methodological contributions. Conceptually, essential heterogeneity is introduced to criminology (Heckman et al., 2006). Essential heterogeneity implies that response heterogeneity is not simply a function of unobserved factors that determine outcomes; it is also a function of unobserved factors that determine the decisions that also impact those outcomes. Moreover, the presence of essential heterogeneity is implied in most, if not all, criminological theories. For example, differential association theory expects criminality to influence social interactions, which then produce criminal behaviors and attitudes, which are also independently affected by criminality. Even previous peer effect estimates produced through well-controlled criminological studies of peer influence are likely to be biased due to the uncontrolled presence of essential heterogeneity.

Methodologically, the current study introduces the local instrumental variables method (Heckman & Vytlacil, 1999, 2005) and a statistical application of it (Brave & Walstrum, 2014) to criminology. Unlike multiple regression and instrumental variables techniques, LIV can estimate causal effects in the presence of essential heterogeneity. Moreover, the individuals to whom those effects apply can be identified. Therefore, as more knowledge about prison peer effects is generated, it may become possible to identify the inmates likely to be harmed by particular prison peer interactions and to identify the inmates likely to be helped by them, so that cellmate allocations that are more efficient with respect to the prevalence of reoffending can be made.

Guide to the Current Study

Estimating the average effect of prison peers on reoffending, as moderated by duration, is the subject of inquiry in the current study, which seeks to understand whether cellmates matter by asking and answering the following question: Does associating with criminogenic cellmates exert time-varying criminogenic effects on released prisoners' reoffending outcomes? That inquiry is organized in the nine chapters that follow.

Chapter 2 reviews the criminological literature, particularly as it pertains to theories of social influence and their application to the study of prison peer effects. Differential association theory, balance theory, and prisonization are discussed, with particular focus on research related to the evolution of prisonization during a prison stay and the potential for those effects to persist post-release.

Chapter 3 reviews the methods, specifically as they apply to causal identification of social interaction effects. Essential heterogeneity is more completely discussed. The local instrumental variables method is introduced as a better solution to the problem of essential heterogeneity than other currently utilized estimation strategies.

Chapter 4 integrates the previous theoretical and methodological reviews into a theoretically-driven analytical framework that is appropriate for the Pennsylvania Department of Corrections context, which is described in Chapter 5. The data available to characterize that context and to create the arrest and reincarceration based outcomes are introduced in Chapter 6. The formal methodological model underlying the LIV framework is outlined in Chapter 7. Limitations of the LIV method, as it is applied in the current study are discussed.

Preliminary analyses are presented in Chapter 8. The analyses presented in Chapter 8 lay the groundwork for the prison peer estimates resulting from the LIV model, which are presented in Chapter 9. The preliminary analyses included in Chapter 8 are: linear probability regression models for the choice and outcome model specifications, justification and validation of the exclusion restrictions, exploration of potential duration thresholds, and an implementation of Heckman et al.'s (2006) test for essential heterogeneity. The prison peer effect estimates presented in Chapter 9 are preceded by a discussion of the support of the propensity score and what it implies for estimation of treatment effects and delineation of duration thresholds. Chapter 10 critically discusses the preliminary analyses and results from Chapters 8 and 9, explores directions for future research, and concludes.

CHAPTER 2: Theoretical Motivation for the Question: Do Cellmates Matter?

> *"Very little is known, even by prison workers, of the kinds of social interaction which take place among prisoners… [T]here has been a growing concern for analysis of this interaction, with the aim of understanding the effects of prison social life on inmates... A number of studies of the prison community have been made, but there has been no systematic effort to develop a system of prison organization based on the results of the studies" (Sutherland & Cressey, 1955, p. 497).*

Since the middle of last century when Sutherland and Cressey (1955) made the preceding observation, very little knowledge has been generated regarding the effects of social interactions between inmates, including whether prison peer effects impact reoffending and how to respond to them to increase public safety. This study hopes to spearhead a twenty-first century criminological inquiry into social interactions amongst prison inmates and their implications for the broader society. Specifically, this study will determine whether associations with cellmates exert criminogenic prison peer effects on the prevalence of reoffending in a cohort of first-time releasees from prison.

Incarceration and Reoffending in Context

Incarceration has become an increasingly dominant public policy response to criminal offending in the United States. It is common knowledge that, in the four decades Blumstein and Cohen (1973) observed that incarceration rates appeared to hold steady over time, the number of people in U.S. prisons and jails at year's end increased from 306K in 1978 to 2.3M in 2010. Over that same period, the incarceration rate increased more than 400% from 141 to 731 per 100,000 (Cantwell, 1980; Glaze, 2011).

The national trend toward the increased use of incarceration to increase public safety and control crime was mirrored in Pennsylvania. According to the Pennsylvania

Department of Corrections (PADOC), the capacity of the state prison system increased by 20%, approximately 12,000 beds, between 2000 and 2007. At year's end in 2007, PADOC alone housed more than 40,000 prisoners.

This public policy response has come at a considerable cost. A recently released National Research Council (NRC) report estimates that states' spending on corrections, exclusive of localities' spending on jails, rose from $6.7B in 1985 to $53.2B in 2010. In 2010 dollars, the states on average invested $37,000 per prisoner per year (NRC, 2014, pp. 314-315). Pennsylvania's citizens invested even more in each inmate. In fiscal year 2010, PADOC had an operating budget of $1.6B, which was overrun by almost half a billion dollars, bringing Pennsylvania's total correctional costs to $2.1B and its per-inmate investment to more than $42,000 (Vera Institute of Justice, 2012). What the citizens of the United States and of Pennsylvania have received in return for their investment in incarceration remains unclear. What is clear from a recent national survey of the public's attitude toward the criminal justice system is that those citizens expect to endure less crime and enjoy more safety (Pew, 2010).

Recidivism is one indicator of the success of correctional systems in their expected and stated goal to preserve public safety by reducing crime through offender rehabilitation and deterrence (Maltz, 1984; Gaes, Camp, Nelson, & Saylor, 2004; Nagin, Cullen, & Jonson, 2009; PADOC, 2013a). Reoffending is also tracked at each level of formal interaction an individual has with the criminal justice system: rearrest, reconviction, and reincarceration. To investigate the effectiveness of incarceration many social science researchers have sought to measure its effect on reoffending at each of those levels, particularly rearrest, which is viewed as the best indicator of reoffending because it involves the least criminal justice system involvement (Maltz, 1984; Langan & Levin, 2002; Gaes et al., 2004; Durose, Cooper, & Snyder, 2014). Unfortunately, while that literature has demonstrated that incapacitation effects are real, it has not yet produced enough credible evidence to support a consensus regarding what effect incarceration has on post-release offending behavior or what might cause that effect (Spelman, 2008; Nagin et al., 2009).

Rote statistics do not suggest that incarceration plays a large role in crime control beyond incapacitating offenders. According to a recent Bureau of Justice Statistics (BJS) report on the recidivism of state prisoners released in thirty states in 2005, 67.8% of the prisoners released were rearrested and 49.7% were reincarcerated within 3 years. Within five years, 76.6% were rearrested and 55.1% were reincarcerated (Durose et al., 2014, p. 15). Again, the statistics in Pennsylvania mirror the national numbers. According to a recidivism report released by PADOC in 2013, six in ten Pennsylvania releasees were either rearrested or reincarcerated within three years. Among the 2006-2007 first-time releasees, 58.5% were rearrested and 46.3% were reincarcerated within the four-year follow-up period. Thus, while it appears that a minority of offenders, approximately one-quarter to one-third, may be rehabilitated or deterred from future crime by a prison stay, the majority is not. Furthermore, determining what portion of the apparent desistance of that one-third of offenders is attributable to the prison stay is methodologically difficult, if not impossible (Spelman, 2008; Nagin et al., 2009).

Spelman (2008) described the difficulties associated with identifying a prison effect from data on incarceration and crime rates. Those difficulties include selection and simultaneity biases. Selection biases can arise from, for instance, comparing individuals who receive prison sentences to individuals who do not because those populations likely differ in ways additional to their experience of prison. Simultaneity bias arises from the inherent reciprocity in the relationship between crime rates and incarceration rates: crime determines incarceration, just as incarceration determines crime.

Spelman (2008) concluded that only one of dozens of studies that tried to causally associate crime and incarceration rates adequately addressed both identification issues, but that it did so without actually answering the question of whether incarceration abates or augments crime. Levitt (1996) estimated an incarceration effect using exogenous judicial release orders as an instrumental variable. Therefore, the effect he identified answered the question of whether crime goes up when prisoners are released early, as opposed to whether it goes down when they are incarcerated. This is an example of what Heckman and Urzua (2010) describe with respect to instrumental variables estimators, more generally: they rarely answer the precise policy question being posed.

Building on a previous systematic review by Villettaz, Killias, and Zoder (2006), which found no evidence of either deterrent or criminogenic prison effects, Nagin et al. (2009) qualitatively assessed the literature on the impact of incarceration on reoffending. Like Spelman (2008), Nagin et al. (2009) concluded that most of the studies they reviewed lacked credibility because they also lacked the methodological rigor to account for selection and simultaneity biases. They followed Spelman (2008) in arguing that instrumental variables approaches provide the best estimates of the causal relationship between incarceration and reoffending because they pay “close attention to the construction of a counterfactual” (Nagin et al., 2009, p. 164). Each of the instrumental variables approaches they deemed high quality exploits a unique policy environment (Drago, Galbiati, & Vertova, 2009; Helland & Tabarrok, 2007).

Drago, Galbiati, and Vertova (2009) exploited a unique policy event, the Collective Clemency Bill, that reduced overcrowding in Italian prisons by releasing inmates early, with the caveat that their residual sentences would be served if they recidivated. Drago et al. (2009) observed a 1.24% reduction in the propensity to reoffend for each additional month of residual sentence. Helland and Tabarrok (2007) estimated the effect of being charged with but not convicted of a second, "strikable" offense in California, which has a three strikes law that mandates a twenty-five years to life sentence after conviction for a third strikable offense. They found that offenders who were convicted of a second strikable offense reduced their reoffending by about 20% relative to those who were charged with but not convicted of a second strike.

As was the case with the Levitt (1996) study, the two "high quality" studies Nagin et al. (2009, p. 164) described similarly elucidate the inability of instrumental variables to answer the exact question being posed, despite the fact that they do answer relevant questions (Heckman & Urzua, 2010). Both studies answered the important question of whether the threat of incarceration deters reoffending in particular policy regimes, one a unique policy event, the other an ongoing policy. Importantly, they did so without confounding the effects of deterrence and rehabilitation (Maltz, 1984; Nagin et al., 2009). However, both studies also failed to address the root question of whether the experience of incarceration suppresses reoffending more generally. Therefore, while these studies suggest that specific deterrence is a palpable phenomenon, they do not demonstrate it. Moreover, if the specific deterrent effects of incarceration are as substantial as these studies suggest, the question of what about or in the incarceration environment has the capacity to subvert them lingers: the question of why incarceration has a "null or criminogenic" (Nagin et al., 2009, p. 115) effect on reoffending remains unanswered.

What Could Explain the Failure of Specific Deterrence?

Nagin et al. (2009) identified at least three theories that could explain why prison might exert criminogenic effects. The first and the one that best fits the context of the current study is that prison can be a learning environment. Learning can refer to the transfer of skills or attitudes from one person or group of people to another such that newer inmates adopt the attitudes and skills of more seasoned inmates by associating with them in environments that allow for dialogue, modeling, reinforcement, and punishment (Sutherland, 1947; Clemmer, 1950; Akers, 2009). For example, inmates who are victimized or see others being victimized in prison might feel more inclined to victimize others upon their release, particularly if they see that those behaviors are rewarded with an increase in social status (Loftin, 1986; Earley, 2000; Spohn & Holleran, 2002; Nieuwbeerta et al., 2009). Alternatively, inmates might use substances to ease their transition to prison, an adaptation that can be reinforced via social interactions with prison peers, and that can create cascading effects in the post-prison domain, as addiction may promote continued criminal behavior (Terry, 2003; MacCoun, Kilmer, & Reuter, 2003; Masten et al., 2005; Staff et al., 2010; Fletcher & Chandler, 2014).

The second theory, labeling, is rooted in symbolic interactionism (Mead, 1934). Labeling theorists argue that individuals in interaction with the social environment begin to adopt the judgments made by others regarding them (Becker, 1963; Matsueda, 1992; Heimer & Matsueda, 1997). Lemert (1951) argued that antisocial behavior is normative in young people but that society's reaction to that initial antisocial behavior (e.g., arrest and incarceration) saddles the individual with a deviant label that creates secondary deviance after the individual identifies with and internalizes the initial deviant label. Moreover, labeling or signaling processes are not restricted to initial deviance, nor are they necessarily always harmful (e.g., Bushway & Apel, 2012). However, the harmful effects of an ex-convict label can have heightened pertinence because former inmates suffer both formal and informal collateral consequences, particularly housing and labor market discrimination, based on that ex-convict signal or label (Pager, 2003; Western & Pettit, 2004; Holzer, Raphael, & Stoll, 2006; Blumstein & Nakamura, 2009). The resultant inability of former inmates to apply for school loans, to find a job, decent housing, or even a suitable marriage partner, it is argued, encourages individuals to persist in, rather than desist from crime because they cannot establish stakes in conformity (Toby, 1957; Travis, 2005; Kling, 2006; Pettit & Lyons, 2007, 2009).

The third theory through which Nagin et al. (2009) allege that prison might lead to criminogenic effects is rooted in the origins of criminological thought. Beccaria (1764) asserted that punishment should be proportional to the offense committed. Similarly, Bentham (1830) argued that "the punishment of imprisonment" is a punishment that, "when applied to slight offences" can, instead of "having a certain tendency to deter from the commission of crime," be observed to "have an opposite tendency…to render those who undergo them still more vicious" (§ VII). Essentially, severe punishments can backfire.

In prison individuals at low risk of continued criminal behavior might experience harsh treatments, which can lead to them to rebel against the perceived unfairness of the system by committing more crime (Sherman, 1993; Gendreau, Goggin, & Cullen, 2000; Winerip & Schwirtz, 2014). This potential criminogenic mechanism has been tested indirectly by the literature that examines whether inmates commit more misconduct in higher security facilities where controls and monitoring are stricter than they are in lower security facilities. While that literature offers the theory little support in that serious misconducts do not seem to occur more frequently in higher security facilities than they do in lower security facilities (Camp & Gaes, 2005; Tahamont, 2013), prison security levels are not the only means through which inmates may suffer harsh treatments that ultimately incite more recidivism or more within-prison violence. The recent attention paid to the vagaries of solitary confinement, for example, reflects this concern, but direct tests of its potential harmfulness have not yet been made (Toch, 2001; Metzner & Fellner, 2010; Mears, 2013; Edge, 2014; NRC, 2014).

Theories of social influence, particularly learning theories, provide the criminological context through which the current econometric analysis of prison peer effects, which is described in more detail in Chapters 3 and 4, is shaped. As the preceding discussion indicated, mechanisms of social influence are not the only means through which the specific deterrent effects of prison might be subverted. They are, however, the primary means through which inmates have been theorized to impact each other's post-prison behaviors.

Criminological theories of social influence, notably differential association and balance theories, provide guidance with respect to how inmates might be expected to generate social interaction effects. They are, therefore, discussed thoroughly in the next several sections, which pay particular attention to key concepts of analytic interest as they apply to the prison context. However, this is not a study of the mechanisms through which social influence operates in prison. It is a study of the prison peer effects exerted during inmate social interactions. The question of interest is whether cellmates generate prison peer effects that impact the reoffending outcomes of a first-time release cohort. Tests of how, specifically, those prison peer effects might be generated are reserved for future work.

Theories and Mechanisms of Social Influence

While social interactions between inmates are not the only means through which prison might subvert deterrence, they have historically been blamed for the failure, or potential failure, of incarceration to reduce reoffending. At the dawn of the use of prisons as punishment, for example, Jeremy Bentham (1830) warned that prisons "instead of places for reform" could become "schools of crime" if "the indiscriminate association of prisoners" were allowed to take place within them (§ VII). Researchers who have sought to explain the failure of imprisonment to deter criminal behavior have returned to this traditional locus of blame (Clemmer, 1940; Gold & Osgood, 1992; Lerman, 2009; Bayer et al., 2009; Nagin et al., 2009). For example, Lerman's (2009) argument that, "Prisons may provide for the transmission of information and skills that make individuals 'better' criminals" (p. 154), echoes Bentham's (1830) assertion that prisons are learning environments capable of fomenting criminal behavior (Clemmer, 1940, 1950; Sutherland, 1947).

Learning theories and the production of criminal behavior through social influence. Sutherland's (1947) seminal criminological theory argues that criminal behavior is a result of differential association to antisocial, as opposed to prosocial, norms, which he called *definitions* (Sutherland & Cressey, 1955; Matsueda, 1988). Differential association itself is a "dynamic, ongoing process of interaction that produces, among other things, criminal acts" (Matsueda, 1988). Sutherland argued that an individual comes to view criminal behavior as favorable because the social group or reference group (Merton, 1957) to which that person associates (or wants to associate) views criminal behavior as favorable. That is, individuals learn to define situations as criminally exploitable when others who are close to them define those situations as criminally exploitable. To define or interpret situations as potentially criminally exploitable, individuals must be familiarized to the definitions or "motives, drives, rationalizations, and attitudes" (Matsueda, 1988, p. 281) favorable toward criminal behavior as well as the skills necessary to execute those behaviors.[1] In short, they must develop their criminality or criminal propensity. Criminality is, therefore, the capacity to define or interpret situations as criminally exploitable. The degree to which individuals have developed their criminality or criminal propensity is reflected in their behavior (Sutherland & Cressey, 1955; Matsueda, 1988; Bushway et al., 2001). Individuals engage in crime when their criminal propensity overcomes their anti-criminal propensity (Sutherland & Cressey, 1955; Matsueda, 1988).

Mechanisms of social influence. According to Sutherland (1947), the mechanisms through which criminality is developed are the mechanisms that support all learning processes. Specifically, he argued that imitation is not the only means through

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[1] Adopting Matsueda's (1988) interpretation of definitions, the current study employs the terms definitions and attitudes interchangeably.

which the skills and attitudes that motivate criminal behavior are developed (Sutherland & Cressey, 1955, p. 79). He further argued that dialogue, both verbal and "of gestures" is a key means through which criminality may be augmented (Sutherland & Cressey, 1955, p. 77). By invoking a dialogue of gestures, Sutherland (1947) appeared to be referencing Mead's (1934, p. 140-1) "conversation of gestures [in which] what we say calls out a certain response in another and that in turn changes our own action." In other words, initial behavior, which may be imitative, is shaped and reshaped through reciprocal social interactions that encourage or discourage continued behavior (Bandura, 1962, Matsueda, 1988; Heimer & Matsueda, 1994).

Early psychological experiments investigated the mechanisms through which social influence encourages and discourages behavior (Skinner, 1953; Bandura, 1962). Those mechanisms include punishment and reinforcement. Punishment and reinforcement operate similarly, but with different goals: reinforcement encourages behavior, while punishment discourages behavior. Both reinforcement and punishment can be applied positively (something given) or negatively (something taken away). Positive reinforcement encourages behavior through application of a pleasing stimulus; negative reinforcement encourages behavior through removal of a displeasing stimulus. Positive punishment discourages behavior through application of an undesirable stimulus; negative punishment discourages behavior through removal of a desirable stimulus.

Bandura, Ross, and Ross (1961) observed that adults modeling aggressive behavior could incite aggressive behavior in children, even absent the presence of reinforcement or punishment of that aggressive behavior. That is, after observing adults' aggressive behavior, the children imitated that behavior. In subsequent experiments, Bandura and his colleagues found that punishment and reinforcement moderated children's tendencies to imitate adults' aggressive behavior. Children who observed adults being rewarded for behaving aggressively more readily reproduced those behaviors than children who observed adults being punished for their aggressive behavior (Bandura, Ross, & Ross, 1963).

Importantly, the children for whom the adults modeled behavior in the latter experiments did not directly experience the punishment or the reinforcement: they only observed it. This suggested that behavior can be reinforced *vicariously*, meaning indirectly, and purely through observation. When people see the behavior of others rewarded, they are more likely to engage in that behavior. When people observe punishment, they are less likely to engage in that behavior (Bandura et al., 1963; Bandura, 1977; Warr & Stafford, 1991; Stafford & Warr, 1993).

Consistent with Sutherland's argument about the generality of learning mechanisms and building on the earlier early work of Skinner (1953) and Bandura (1962), Burgess and Akers (1966) elaborated upon Sutherland's theory by articulating and describing the modeling, reinforcement, and punishment processes that support all learning and, with it, the production of criminal attitudes, skills, and behaviors. Imitation of modeled (i.e., observed) criminal behavior is reinforced or punished. Reinforcement and punishment can take many forms. Among them Burgess and Akers (1966) list "social attention, approval, affection, and social status" (p. 133), which can be given or taken away. That reinforcement and punishment, particularly when repeated in consistent situations, facilitates and cements learning has been borne out in the psychological literature that has emerged the fifty years since Burgess and Akers (1966) outlined their initial argument (e.g., Akers, 2009; Kahneman, 2011).

In contrast to Sutherland (1947), Burgess and Akers (1966, p. 137) argued that verbal communication would not, on its own, instigate changes in behavior. They argued that verbal communication of skills and attitudes, like modeled behavior, needs to be reinforced or punished repeatedly and consistently to affect lasting behavioral change (e.g., Skinner, 1953). However, through coterminous dialogue, verbally communicated attitudes and skills can be near-concurrently punished, reinforced, or rationalized using the socialization mechanisms articulated by Burgess and Akers (1966). This happens naturally in group-based and one-on-one conversations as the participants in those conversations react to statements made by each other. Those reactions can serve as powerful motivators for attitudinal change, as they can punish and reward (Mead, 1934; Asch, 1952; Bandura & McDonald, 1963; Bormann, 1972; Shiller, 1995; Hartup, 2005).

In early replications and extensions of differential association theory, Cressey (1952) and Matza (1964) empirically demonstrated that both verbal communication and rationalizations of behavior play roles in the development of criminal definitions. Rationalizations diminish the notion that one's behavior causes harm. Verbalizing those rationalizations in groups can make impermissible behavior permissible, thus reinforcing it. Similarly, dialogue that is intended to evoke deviant behavior, or *deviancy talk*, has been specifically implicated as a vehicle through which deviant attitudes and behaviors are both learned and reinforced (Dishion, Spracklen, Andrews, & Patterson, 1996; Dishion & Dodge, 2005, p. 397; Dishion & Dodge, 2006, p. 29). By discussing deviant behavior, it is encouraged and rationalized, particularly via techniques of neutralization

(Matza, 1964), which diminish the perceived harm criminal behavior may do to others and to oneself. Through dialogue, modeling, and reinforcement processes, offenders may, therefore, learn new skills and adopt new definitions that lead to new criminal behaviors or their previously learned skills, attitudes, and behaviors may be reinforced (Matsueda, 1988; Hartup, 2005).

Who influences whom? Implicit in Sutherland's (1947) theory is the notion that more criminally experienced offenders influence less criminally experienced offenders. To paraphrase, Sutherland argued that criminal behavior is learned, not inherited (Sutherland & Cressey, 1955, p. 77). This implies that an individual who does not possesses criminal definitions (i.e., attitudes) and the skills to exercise those attitudes must, through learning processes like dialogue, modeling, punishment, and reinforcement, acquire those skills and attitudes from individuals who already possess them. Once acquired, those skills and attitudes can be applied to criminal behavior or not, depending both on the degree to which the individual's criminal propensity is countervailed by his anti-criminal propensity and whether he perceives situations in which he finds himself to be suitable for criminal exploitation based on those propensities.

Sutherland also suggested that the adoption of criminal definitions and skills would lead to ever-more susceptibility to criminality, just as the adoption of prosocial attitudes and skills would lead to ever-more susceptibility to prosociality. As Matsueda (1988, p. 283) summarized, "Sutherland hypothesized that differential receptivity is determined by the person's current ratio of learned behavior: Those who have learned an overabundance of anticriminal definitions will be receptive to additional anticriminal definitions and resistant to procriminal definitions, and vice versa." This seems to suggest a near-unidirectional process, whereby the criminally-inclined become continuously more disposed toward criminality after that point of overabundance of criminal definitions over anticriminal definitions is reached. In criminology, this unidirectionality had been nearly always presupposed (and, according to Hartup (2005), is the more prevalent perspective in the psychological literature) until McGloin (2009) presented her theory of delinquency balance.

Delinquency balance theory accounts for the fact that peers can instigate or reinforce positive behaviors and outcomes, just as they can negative ones (e.g., Barry & Wentzel, 2006; Massey, Gebhardt, & Garnefski, 2008) and that those effects depend on the characteristics of the peers in question (Hartup, 2005; Mouw, 2006). McGloin (2009) argued that the level of delinquency or criminal experience of an individual matters, as does the relative distance between his level of criminal experience and the level of criminal experience of the peer with whom he interacts. The potential effect that a peer will have on an individual can only be determined relative to the individual, such that the individual and his peer moderate toward each other to achieve equilibrium. Thus, interactions with the same peer can incite criminality in a less criminally experienced individual, while abating criminality in a more criminally experienced individual. Through the interaction of their criminal experiences, the outcomes of the individual and his peer are determined.

Delinquency balance theory accords with differential association theory and the broader peer literature in that it assumes that peer influence is predicated on the "intimacy or importance" (McGloin, 2009, p. 445) ascribed to the peer relationship (Sutherland, 1947; Agnew, 1991; Warr, 2002). Sutherland asserted that "[t]he principal part of the learning of criminal behavior occurs within intimate personal groups" where the intensity or prestige of the relationship plays a role in the transmission of attitudes and behaviors (Sutherland & Cressey, 1955). However, there is ample evidence to suggest that, while intimacy may moderate or exacerbate peer influence, it is not a necessary precondition of it (Clemmer, 1940; Heider, 1958; Hartup, 2005; An, 2011).

In developing his seminal balance theory, Heider (1958) took a more catholic approach to the nature of peer influence, stating, "[t]he tendency toward equalizing the fortunes of [an individual] and [his peer] may or may not be concordant with the sentiment relations between them" (p. 289). That is, peer influence can emerge in relationships characterized by antipathy or indifference, just as it can emerge through intimacy and affection (Hartup, 2005; An, 2011). Moreover, the ties between individuals do not have to be strong or direct, as argued by Granovetter (1973), for the effects of social influence to theoretically emerge. In fact, Hartup (2005, p. 389-91) acknowledges that the potential emotional drivers of social relationships and their potential capacity to exert social influence are poorly understood. Nevertheless, likely due to Sutherland's seminal influence, the focus of the criminological study of social influence has typically been intimate peer groups (e.g., friends, friends of friends, social networks) and dyads, where affection or, at the very least, similarity (i.e., homophily, homogamy) are presumed to motivate peer interactions and their effects (Gans, 1961; Hirschi, 1969; Cohen, 1977; Kandel, 1978; Haynie, 2001; McPherson, Smith-Lovin, & Cook, 2001; Weerman & Smeenk, 2005; McGloin & Shermer, 2009).

The dyadic relationships most often explored in the criminological and sociological literatures that reference crime and delinquency are best friendships (e.g., Jussim & Osgood, 1989; McGloin, 2009) and intimate partnerships (e.g., Haynie, Giordano, Manning, & Longmore, 2005; Kreager & Haynie, 2011). Contrary to Sutherland (1947) who implied that more intense best friendships would generate larger social interaction effects (e.g., Hartup, 2005), Warr (2002) argued that best friends might exert lesser social influence because they are more loyal to each other and, therefore, less willing to ridicule each other, which he argued is a primary means through which behavior is transformed (e.g., Braithwaite, 1989). Rees and Pogarsky (2011) tested Warr's (2002) hypothesis that best friends would not exert as much influence as their peer group. They found that both best friends and their peer groups mattered in the production of several outcomes: delinquency, smoking, drinking, and fighting. The magnitude of the effects associated with both best friends and peer groups was substantial and significant, ranging from 10-20% increases for most outcomes.

The equivocal results of the Rees & Pogarsky (2011) study effectively summarize the broader literature related to the relative influence of single peers (e.g., best friends) and peer groups. Among studies that compare the influence of best friends to that of their social group or network, some have found that the influence of best friends dwarfs that of the social group (Urberg, 1992; Hussong, 2002), whereas others have found the effects of single peers to be more prominent (Kandel, 1978). Like Rees and Pogarsky (2011), other studies, particularly more recent studies, have reported equivocal effects (Weerman & Smeenk, 2005) that support peer influence for both types of relationships, but that were also highly context and outcome dependent (Simmons-Morton & Farhat, 2010; Brechwald & Prinstein, 2011; Giletta et al., 2012).

Moderators of learning effects. As alluded to earlier, Sutherland (1947) identified characteristics of associations that are likely to moderate their impact on the individuals involved in them. He discussed four such characteristics: intensity, frequency, priority, and duration. Unfortunately, he did not precisely define these potential "modalities of behavior" (Sutherland & Cressey, 1955, p. 78). Nor did he describe how they might relate to or be distinguished from each other. In fact, Sutherland asserted that duration and frequency "are obvious and need no explanation" (Sutherland & Cressey, 1955, p. 78). This is unfortunate because both frequency and duration, as commonly understood, have the potential to be confounded with priority and intensity, as Sutherland loosely described them.

Sutherland conceptualized priority as associations initiated early in life (or earlier than comparative associations), which can clearly be confounded with duration or the length of time an association lasts (Warr, 1993). Similarly, the intensity or the "prestige" or the "emotional reaction" associated with an association (Sutherland & Cressey, 1955, p. 78) can be confounded with the propensity to endure in or leave an association and with the willingness interact more or less often with that associate, as the preceding discussion of best friends illustrated.

While duration can be confounded with both intensity and priority, Sutherland (1947) also conceived it straightforwardly. Duration is expected to moderate the effect of social influences, such that, to paraphrase Warr (1993, p. 33), "exposure to [social] influences over prolonged periods has a greater effect than exposure over more limited periods." This suggests that social interaction effects may be small, even undetectable, at first, but that they continue to grow over time. Sutherland did not specifically discuss the rate at which social interaction effects might grow or whether they should be expected to continue to grow at the same rate as time progresses. Nor has that aspect of duration been examined in the criminological or sociological peer literatures.

Despite its simplicity and the importance ascribed to it in Sutherland's (1947) seminal criminological theory, the average effect of the duration of social relationships on the social interaction effects they might generate has only rarely been examined in the criminological and sociological literatures. Although the knowledge base is small, it is consistent with the hypothesis that there is a positive relationship between duration of association with peers and the magnitude of social interaction effects. The early work of Short (1956, 1958) found moderate ($\rho \sim 0.4$) correlations between having long-term friends who were delinquent and individuals' self-reported delinquency. Agnew (1991) showed that spending more time with delinquent peers increases own delinquency. And Warr (1993) found an association between delinquency and the increasing amounts of time juveniles spend with their peers as they age.

Only one other study that specifically examined the effect of relationship duration on antisocial behavior was identified through the current review of the literature. Using the AddHealth (Harris et al., 2009) data, Haynie et al. (2005) assessed the effect of the duration of romantic relationships on minor and serious delinquency. The adolescent romantic partnerships they studied lasted on average 9.6 months (SD=10.25). The relatively short duration of those adolescent romantic relationships was positively and directly related to serious delinquency, independent of the romantic partner's delinquency, and also indirectly through the interaction with the romantic partner's delinquency. For minor delinquency, relationship duration had a positive impact only indirectly through the interaction with the romantic partner's delinquency. Beyond Warr's (1993) interpretation of Sutherland's (1947) intent (i.e., a positive relationship between duration and social interaction effects) and the limited studies in this review, criminological theory provides little guidance regarding the direction and magnitude of moderating effects that duration should be expected to generate. There is, however, reason to question that duration would exert homogeneous (i.e., the same for all individuals) and ever-increasing effects on social influence.

While McGloin's (2009) balance theory does not address the potential temporal elements of peer relationships, it has implications for them. As an individual and his peer seek balance within their relationship, when that equilibrium is reached (i.e., when the attitudes and skills and behaviors of an individual and his peer become congruent), the empirical implication is that social interaction effects will become undetectable. Moreover, as the relative distance between an individual and his peer diminishes, evidence of the social interaction effect must also diminish because the distance to be traversed is smaller. With respect to duration, this suggests that initially increasing social interaction effects will peak and eventually begin to decrease over time until they become undetectable: they will have a parabolic or semi-parabolic shape. At the very least, as individuals attempt to achieve congruence with their peers, initially increasing social interaction effects should be subject to diminishing marginal returns as the association approaches congruence.

How long might peer effects persist? Neither differential association, nor social learning, nor balance theories make strong predictions about the persistence of peer effects that result from learning mechanisms. That is, criminological theories of social influence do not make clear predictions regarding how long peer effects should remain detectable. However, the mechanisms of social learning, which upon which the aforementioned criminological learning theories rest, have been theorized to generate effects that can cascade through multiple contexts, such that they remain or become detectable over short (e.g., months) and long (e.g., years, decades, and even generations) periods of time (Masten et al., 2005; Masten & Cicchetti, 2010; Dishion et al., 2010; Dishion, 2014). In the context of developmental cascades, there is no theoretical time limit on the potential for social interactions to exert effects.

Developmental cascades. As Masten and Cicchetti (2010) define them, "*Developmental cascades* refer to the cumulative consequences for development of the many interactions and transactions occurring in developing systems that result in spreading effects across levels, among domains at the same level, and across different systems or generations" (p. 491, emphasis in original). Cascade theory is rooted developmental dynamic systems theory, as developed from the natural sciences literature by Thelen (1990), who argued that complex, nonlinear processes of individual interaction with the social environment generate individual differences in behavior. The effects due to developmental cascades persist because they alter the course of development, such that "an early advantage or disadvantage in one…domain influences another later developing and high order domain" (Masten & Cicchetti, 2010, p. 492). While, as noted by Masten and Cicchetti (2010), the terminology used to describe cascade-like processes varies by discipline, the basic premises that they argue underlies developmental cascade theory are present in burgeoning literatures in the social sciences (Cunha & Heckman, 2008; 2010; Krohn, Ward, Thornberry, Lizotte, & Chu, 2011). For example, in their synthesis of the developmental literature, Cunha, Heckman, Lochner, and Masterov (2006) argue that learning process exhibit self-productivity, which means early skill acquisition facilitates later skill acquisition, and dynamic complementarity, which means early investments facilitate later investments. Together, self-productivity and dynamic complementarity explain how learning cascades or, in Cunha et al.'s (2006) parlance, "skill begets skill through a multiplier process" (p. 698).

Developmental cascades and criminological learning theories. Differential association and balance theories implicitly invoke cascading effects because they invoke learning processes that are theorized to follow cascade processes, whereby skills and attitudes acquired at an earlier time in one domain can be applied and augmented at later time periods, and across multiple domains (Fry & Hale, 1996; Masten et al., 2005; Bornstein et al., 2006; Cunha, et al., 2006; Cunha & Heckman, 2008; 2010; Dishion et al., 2010; Dishion, 2014). Differential association theory, which argues that delinquent definitions beget delinquent definitions, accords with a unidirectional cascade conceptualization in which previous antisocial behavior lays the groundwork for continued antisocial behavior (Sutherland & Cressey, 1955; Matsueda, 1988). Learning cascades can also be bidirectional (Masten & Cicchetti, 2010), which accords with the expectations of balance theory (McGloin, 2009). Furthermore, many cascade-based theories, such as Dishion et al.'s (2010) social augmentation hypothesis, rely on the social learning mechanisms through which differential association and balance theory expect social interaction effects to arise (Brody et al., 2010; Lansford, Malone, Dodge, Pettit, & Bates, 2010). The social augmentation hypothesis of Dishion and his colleagues (2010) argues that the development of antisocial behavior is a progressive process that unfolds over time and, specifically, through interactions with deviant peers who engage in deviancy training. This developmental pathway and its potential to be adapted to the prison context to explain the persistence of prison peer effects are discussed later in the current chapter.

Learning Theories in the Prison Context

> *"American prisons contribute in some degree to the criminality of those they hold" (Clemmer, 1950, p. 311).*

While Sutherland (1947) argued that socialization through ordinary learning mechanisms could foment criminal behavior outside prison, Clemmer (1940, 1950) argued that socialization to prison norms through ordinary learning mechanisms could amplify post-prison criminal behavior. He coined the term *prisonization*, which he characterized as "fundamentally a learning process" (Clemmer, 1950, p. 318), to describe the socialization of inmates to the prison environment, which he characterized as oppositional to prosocial norms (e.g., compliance with correctional officers).

Clemmer's prisonization model became known as the *importation* model because he viewed prisonization as mainly a function of the characteristics inmates have upon admission to the prison system (Wellford, 1967). Clemmer (1940, 1950) expected preexisting inmate characteristics to both create variation in prison environments and to help to determine individual assimilation to the norms within it, such that both the characteristics of the individual inmates and the characteristics of their prison peers matter in the prisonization process (e.g., Hartup, 2005; McGloin, 2009; Mears, Stewart, Siennick, & Simmons, 2013). The attitudinal and behavioral modification processes of prisonization "breed" criminal behavior that is exhibited after prisoners are released (Clemmer, 1950, p. 318), such that prisoners "go forth in tragic numbers to engage in crime again… [and] the later crimes of those who have been in prison are frequently more sophisticated or heinous than the offenses for which they were first committed" (Clemmer, 1950, p. 313).

Mechanisms of prison peer influence. While it is generally assumed that opportunities for modeling criminal behavior and skills may be more limited in the prison context, both ethnographic evidence and empirical studies of prison misconduct suggest that there is no shortage of criminal activity inside prisons. Prison misconduct studies report that about one-third of prisoners are convicted of serious misconduct offenses that have parallels in the outside environment such as assault, arson, threatening correctional officers, drug trafficking, extortion, and bribery (Camp & Gaes, 2005; Tahamont, 2014). The prevalence of these serious misconduct convictions suggests that even in highly structured and closely monitored prison contexts, opportunities for criminal and antisocial behaviors can arise frequently, which further suggests that opportunities for criminal behavior, its punishment, and its reinforcement, whether experienced directly or observed vicariously (Skinner, 1953; Bandura, 1962; Burgess & Akers, 1966), are prevalent in the prison environment. However, even if opportunities for explicitly modeling criminal behavior and technical skills are more limited inside prison than they are outside it, attitudes can still be modeled and reinforced and criminal skills and behaviors can be discussed and reinforced, as described by Earley (2000).

"Most convicts, I soon learned, try to avoid trouble and simply do their time as easily as possible. But about twenty percent of the inmates operate inside the prison much the same as they did on the streets. They deal drugs, extort money, bankroll card and dice games, pimp, and run scams on other inmates. These inmates are known predators. Their victims are called lops. The line between the two groups shifts daily" (Earley, 2000, p. 38).

Even if opportunities for modeling behavior are more limited in the prison context than they are outside prison, criminality can still be transmitted via dialogue. Clemmer (1940, p. 87) argued that communication, "the method by which ideas are exchanged through language (speech and writing)" is another a primary means through which prisonization occurs. Moreover, criminological studies have also shown that in closed, incarceration-like environments, social interactions between program participants have impacted their criminal attitudes, later criminal behavior, and other deleterious behaviors, such as substance abuse and mental health (McCord, 1978; Gold & Osgood, 1992; Tita et al., 2010).

McCord's (1978) 30-year follow-up of the Cambridge-Somerville study found that the programmatic interventions meted out to groups of male juveniles harmed them later in life by increasing their mortality, substance abuse, and other negative physical and mental health outcomes. Her work, in combination with short-term findings indicating that a group-based delinquency prevention program in North Carolina harmed its participants, prompted the observation that concentrating groups of delinquent individuals together for treatment purposes might backfire and, ultimately, increase their criminality (Dishion, McCord, and Poulin, 1999; See also: Gold & Osgood, 1992; Tita et al., 2010). To account for this phenomenon, Dishion and his colleagues developed deviant peer contagion theory (Dishion & Dodge, 2005; Dodge, Dishion, & Langford, 2006).

Deviant peer contagion theory argues that a reciprocal process of reinforcement of antisocial behaviors and attitudes that operates through dialogue can undermine the therapeutic aims of group-based interventions, especially those that take place in correctional environments. As such, deviant peer contagion is fundamentally a learning theory that operates through ordinary learning mechanisms, particularly a form of dialogue called deviancy talk. Deviancy talk is dialogue that promotes deviant behavior by reinforcing (Skinner, 1953; Bandura, 1977) and rationalizing (Matza, 1964) it. Moreover, deviant peer contagion theory is rooted in modern observations, such as that of Gold & Osgood (1992) below, which echo Bentham's (1830) near-200 year-old concerns.

> *"It is generally assumed that peer influence among incarcerated offenders is likely to interfere with attempts to bring about their reform" (Gold & Osgood, 1992, p. 15).*

While they did not directly test the as-then undeveloped theory, Gold and Osgood's (1992) work with juveniles in Michigan's correctional facilities suggests the presence of deviant peer contagion. They found general increases in deviance despite the boys' participation in a program that was designed to combat negative peer influences in therapeutic group settings. More recent studies suggest that deviant peer contagion may be offense-specific, rather than a process that affects behavior more generally (Lee & Thompson, 2009; Bayer, et al., 2009; Mennis & Harris, 2011). For example, Bayer et al. (2009) found crime-specific effects whereby juveniles housed in facilities with other juveniles who committed similar crimes were more likely to recidivate with the same offense than were juveniles housed in facilities with fewer similar offenders.

> *"Every inmate talks freely only with some other inmate. Each knows the other's crime. There is no reticence over the discussion of crime. Everyone feels unashamed where everyone else has the same cause of shame. No matter how diverse the crimes may be, they are cast into a common pool of shamelessness…this hardening of the conscience, which has its origin in a popular boasting of crimes committed and a brazen bragging of new crimes planned for the first opportunity of freedom" (Higgins (1920) as cited in Sutherland & Cressey, 1955, p. 505).*

Although typically applied to juveniles, deviancy talk and deviant peer contagion may also operate among adults. That is, among adults, deviancy talk may become criminality talk, as suggested by Higgins (1920) when he alluded to a "hardening of the conscience" that appears akin to techniques of neutralization theorized by Matza (1964). Moreover, there may be more opportunities for criminality talk and fewer opportunities for inmates to be shamed or ridiculed (Warr, 2002) out of antisocial and into prosocial behavior. That is, inmates may be in a "common pool of shamelessness" where that type of ridicule either does not arise or cannot arise due to oppositional prison norms that reject prosocial values such as cooperation with correctional officers (Clemmer, 1940, 1950; Sykes, 1958).

Who influences whom in the prison context? The differential in differential association implies that differences between associates generate the differences in criminal skills, attitudes, and, ultimately, behaviors observed within populations, even prison populations. However, prison peers who are more experienced can be challenging to differentiate in the prison environment where, by virtue of their common status as inmates, all potential prison peers have been convicted of at least one, and generally multiple, crimes. As Clemmer (1950, p. 319) put it, "Most persons admitted to prison already possess 'criminality' in various degrees." Still, based on their incarceration histories, arrest histories, and background characteristics (e.g., employment, substance abuse, education, and age) inmates who have more criminal experience and inmates who are more likely to pose a higher risk of recidivating (i.e., evince higher degrees of criminality) can be differentiated from inmates with lesser criminal experience and lower risk of recidivating.

Associations with more criminally-experienced and criminal offenders, in terms of their offending histories and observed criminality (i.e., risk of recidivism), are the inmate relationships hypothesized to generate criminogenic social interaction effects on the members of the first-time release cohort under study. Even though they do not directly or completely measure it, the criminal behaviors and general life circumstances of an inmate are related to his underlying criminality, or propensity to engage in criminal behavior as a result of his differential association to more experienced offenders and offenders with higher levels of criminality from whom he may acquire criminal and antisocial skills and attitudes (Sutherland, 1947; Matsueda, 1988; Gottfredson & Hirschi, 1990; Bushway et al., 2001; Gaes et al., 2004).

Prior prison sentences are both indicative of serious prior criminal behavior and the failure of punishment to deter continued criminal behavior. This combination suggests both more criminal experience and a higher degree of criminality on the part of inmates with prior prison sentences. By virtue of the fact that it incurred the most stringent sentence society can impose, the behavior that resulted in a prior incarceration is likely to have been serious, whether it was a single very serious offense (e.g., manslaughter) or a persistent pattern of repeating lower-level offenses (e.g., petty theft). Continued criminal behavior that leads to reincarceration suggests heightened criminality or a pronounced overabundance of criminal definitions because it demonstrates resistance or imperviousness to the deterrent or reforming effects of the prison sanction (Sutherland, 1947; Blumstein et al., 1986; Anwar & Loughran, 2011). Potential exceptions are sentences imposed on drug offenders (Reuter, 1992; Sevigny, 2009). The harsh punishments meted out to drug offenders during the study period between 2000 and 2007 were and are considered controversial and may reflect moral panic or political pressures to appear tough on crime, rather than truly serious criminal offending (Blumstein & Beck, 1999; Caplow & Simon, 1999; Raphael & Stoll, 2009; NRC, 2014).

In the prison context, more criminally inclined inmates with one or more prior incarcerations on record might also have particular influence over first-time releasees due to their status or, as Sutherland characterized intensity, prestige in the prison context (Clemmer, 1940, 1950; Sutherland, 1947, p. 79). According to Clemmer (1950, p 316), all men become prisonized to some degree. Cellmates with prior prison experience, therefore, are more likely to have assimilated to the prison culture, which Clemmer (1950) observed to be non-cooperative, oppositional to societal norms, and assaultive in nature (Wheeler, 1961). Reincarcerated inmates are also more likely to assume leadership roles in the prison social hierarchy, roles through which criminal attitudes and skills may more readily be transmitted (Clemmer, 1938; Schrag, 1954; Wellford, 1973; Crewe, 2007; Skarbek, 2014). In fact, Wellford (1973) observed that prison leaders, defined as inmates with more social connections than other inmates, are more likely to be prisonized than are other inmates, as were inmates who had committed more prior offenses.

Even if they are not prison leaders or have not been formerly incarcerated, some inmates can still have more experience committing crimes than do others. Inmates who have committed fewer crimes may be less criminally connected to sources of attitudes and behaviors that facilitate those crimes, while inmates who have committed more crimes may be more criminally connected to those influences. Gangs and informal social networks, both within prison and outside prison, can provide the influences that tend to lengthen criminal records (Jacobs, 1973; Haynie, 2001; Fleisher & Decker, 2001; Pyrooz, Decker, & Fleisher, 2011; Skarbek, 2014). Similarly, more experienced inmates (i.e., those who have been arrested or incarcerated more frequently) may also be more ingrained in an external criminal culture that they import to the prison context, where their criminal values influence less experienced criminals (Clemmer, 1950; Wellford, 1967; Anderson, 1999; Mears, et al., 2013). By interacting with individuals who possess more of these kinds of personal criminal capital, first-time inmates may more readily develop the technical skills, personal charisma, and the social contacts to commit more crime after their release (McCarthy & Hagan, 2001).

> *"[Halfpint] was the wisest prisoner I ever knew. I compared myself with him and saw the difference. He was a con man, who at one sweep of his hand could make enough dough to live on for the rest of his life, while I, a petty thief, could hardly steal enough to live on…I could see that among criminals he was respected and a hero. I felt humiliated inwardly, and made up my mind to get a racket that would bring me good returns. Halfpint promised to help me in working out my plans, and I had a whole year to do it in…I planned to pull off a pay-roll job at a firm where I had worked…I figured I'd make one big haul and then be sitting on top of the world" (Shaw, 1966, p. 152-4).*

This seemed to have happened for Stanley, a low-level robber in Shaw's (1966) seminal ethnography. He observed what differentiated himself from his more experienced cellmate, Halfpint, both in terms of Halfpint's criminal experience as a more sophisticated con man and his stature in prison, which presumably proceeded in part from his criminal experience. Stanley wanted to emulate both Halfpint's criminal endeavors and his ability to command respect. Over the course of his prison stay, Stanley began learning how to commit more sophisticated crimes from Halfpint, going so far as to plan a crime on the inside that would take place on the outside.

> *"When new [inmates] come into prison … they are really educated by their peers," said Slack, "[M]ost hook up with someone and find out the unwritten rules---where to eat in the dining room, who's a snitch, who they can trust. We are both caught in the same world where there are rules and then there are rules" (Earley, 2000, p. 231, emphasis in original).*

Prison peer influence and first-time inmates. As Shaw (1966) and Earley (2000) reported, ethnographic evidence suggests that first-time inmates learn how to conduct themselves in the prison environment primarily by observing the behavior more experienced inmates who have already assimilated to that context and excelled socially within it (Nelson, 1933; Clemmer, 1938; Wellford, 1973; Earley, 2000; Jones & Schmid, 2000; Santos, 2006). By modeling the non-cooperative, oppositional, and/or assaultive behavior of their prison peers, first-time inmates can more readily integrate into the prison context (Bandura, 1961, 1962; Clemmer, 1938, 1950; Adams, 1992). To echo Burgess and Akers (1966), the attitudes and behaviors inmates display may be rewarded with varying degrees of the prison equivalents of "social attention, approval, affection, and social status" (p. 133). As a result of receiving these social rewards, first-timers may develop greater criminal propensity, particularly if their behavior is rewarded in close association with a more experienced cellmate, whose influence is theorized to be greater (Sutherland, 1947; Clemmer, 1950; Bandura, 1963; Gold & Osgood, 1992; Kahneman, 2011). These general processes may explain Nieuwbeerta et al.'s (2009) finding that first-time inmates committed more crimes relative to similarly-situated offenders who were not subject to incarceration, as described by Wheeler (1961).

> *"If the process of prisonization is operating effectively we should be able to observe its effects over shorter time periods. And we would expect the effect to be present particularly for offenders serving their first term in an adult penal institution" (Wheeler, 1961, p. 702).*

Prison peer effect predictions. Differential association and balance theories predict that less criminal inmates, such as those have never been incarcerated or who appear to have committed fewer crimes, will experience attitudinal shifts toward and acquire technical skills related to the criminal behavior of the more criminal prison peers with whom they interact. The criminal behavior of the inmate with lesser experience will be exacerbated. In contrast to differential association theory, balance theory also makes a clear prediction regarding the behavior of the inmate with more criminality: his criminality should be reduced after interacting with less criminal inmates (i.e., he should equilibrate toward his less criminal prison peer).

Differential association is less clear about what to expect of the behavior of the inmate with more criminality because the theory offers no explicit prediction regarding whether individuals can unlearn criminality. A prediction can, however, be inferred. Sutherland (Sutherland & Cressey, 1947, p. 78) predicted that individuals whose criminal definitions exceed their anti-criminal definitions will "become" delinquent. He also predicted that individuals who have acquired some criminality are prone to acquiring still more criminality (Matsueda, 1988). However, recognizing that learning processes apply to all behaviors, and not just to criminal behaviors (Sutherland & Cressey, 1947, p. 79), means recognizing that anti-criminal behaviors can be accumulated just as readily as criminal behaviors can. An implication of that recognition is that the balance between criminal and anti-criminal definitions may experience periods of both stability and change, such that the balance of definitions in the criminal or in the anti-criminal direction shifts. Moreover, although the tendency may be to extend the advantage of whichever class of definitions, criminal or anti-criminal, dominates that tendency does not imply that that the weaker class of definitions cannot itself be strengthened and eventually overwhelm the dominant class. Therefore, even in a differential association framework, less criminal prison peer influences should produce crimino-suppressive, as opposed to criminogenic prison peer effects.

Duration, prisonization, and prison peer effects. The concept of time is implicitly connected to prison effects and, hence, to prison peer effects, for the obvious reason that inmates are sentenced to prison for particular periods of time. In their review of the incarceration and reoffending literature, Nagin et al. (2009) specifically focused on the failure of criminologists to provide dose-response estimates of the effect of incarceration on reoffending. That is, the question of whether increasing amounts of time served exert criminogenic or crimino-suppressive effects had gone unanswered. Since 2009, several dose-response estimates of the effect of incarceration on reoffending have been provided. Each of those estimates relies on propensity score matching designs and each confirms that shorter sentences have null effects on reoffending (Loughran, et al., 2009; Snodgrass, Blokland, Haviland, Nieuwbeerta, & Nagin, 2011; Meade, Steiner, Makarios, & Travis, 2013). One suggests that sentences longer than five years may have crimino-suppressive effects (Meade, et al, 2013).

Like prison effects, prison peer effects have been theorized to be time-dependent. Clemmer (1940, 1950), like Sutherland (1947), predicted a positive relationship between duration of association and socialization. He expected that longer spells of incarceration would increase the degree of prisonization of inmates. In the dose-response parlance of Nagin et al. (2009), as the dose of time in prison increases, the criminogenic reoffending response should increase. Moreover, according to Clemmer (1940, 1950), differential association with other inmates is the main mechanism through which prisonization operates (Wheeler, 1961; Wellford, 1967). Clemmer (1940) expected prison peers to promote prisonization, such that evidence of prisonization should emerge slowly and continue to grow over time as incoming inmates assimilate into the prison social milieu.

Duration and prisonization. In a cross-sectional study designed to examine the relationship between prisonization and time spent in prison, Wheeler (1961) presented young adult (aged 16-30) inmates with hypothetical vignettes intended to elicit their level (high, medium, or low) of adherence to the oppositional (to societal norms and correctional officer expectations) and antisocial inmate subculture observed by Clemmer (1940) and Sykes (1958). For example, he asked inmates whether they would approve of working hard, revealing other inmates' escape plans, and hiding contraband from correctional officers. Inmates' agreement with antisocial and oppositional norms was taken as evidence of prisonization. The inmates' degrees of prisonization were then related to the amount of time each had been in prison and to the amount of time he had left to serve.

As expected, Wheeler (1961) observed a time-dependent process of assimilation that results in "internalization of a criminal outlook" (Wheeler, 1961, p. 697), as individuals acclimated to and, in most cases, developed relationships in the prison community (e.g., Sutherland & Cressey, 1955, p. 503). However, contrary to Clemmer's (1940) expectation that prisonization would continue over the course of prisoners' stays, Wheeler (1961) also found that prisonization eventually decreased with respect to time served. Thus, Wheeler (1961) found an inverse U-shaped relationship between time spent in prison and prisonization,[2] such that prisonization appeared to peak near mid-sentence, and then subside as an inmate approached his release date. This shape applied to both first-timers and recidivists, although as predicted by Clemmer (1940), recidivists both entered and exited prison evincing higher levels of prisonization.

Like Wheeler (1961), Wellford (1967) found a significant relationship between time spent in prison and prisonization, with a weakening association between prisonization and time served as inmates' neared the ends of their sentences. However, Wellford (1967) also found that an inmate's criminal social type (anti-criminal, pro-criminal, or unclassifiable) exerted an effect on prisonization that was both stronger than and independent of the duration of incarceration. As a result, he ascribed paramount

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[2] Wheeler (1961) and his contemporaries measured not prisonization with respect to antisocial norms, but adherence to prosocial norms (i.e., staff expectations), so they found a U-shape, meaning a dip in prosocial attitudes at mid-sentence. The analogous prisonization (i.e., more antisocial attitudes) curve would have an inverse U-shape.

importance to the "characteristics of the individual prior to his commitment," which he asserted "chiefly determined" his "level of prisonization" (p. 202-3).

Glaser and Stratton (1961) added an additional insight that accords with Wellford's (1967) hypothesis. In contrast to Wheeler (1961), who argued that time to release from prison, not time spent in prison, was the determining factor in prisonization, Glaser and Stratton (1961) argued that time spent in prison did not independently affect prisonization. Instead they emphasized the *interaction* between time spent in prison and prison peer influences in producing prisonization effects.

Echoing Sutherland (1947) and Merton (1957), Glaser and Stratton (1961) implicated the reference groups toward which inmates orient themselves at different points in their prison stays. They hypothesized that inmates refer to other, presumably antisocial, inmates upon entering and during the process of acclimating to prison. As they approach their release dates inmates orient toward, presumably prosocial, reference groups exterior to the prison (Glaser & Stratton, 1961, p. 389). Therefore, just as Warr (1993) found that spending more time with delinquent peers increases delinquency on the outside, Glaser and Stratton (1961) argued that spending more or less time in association with other inmates may help to determine the evolution of prisonization during a prison stay. Wheeler's (1961) findings supported their hypothesis: he found less evidence of prisonization and shallower prisonization curves among those inmates who reported spending less time with other inmates.

The work of Wheeler (1961) and his contemporaries offers insight into how socialization processes in the prison context may unfold. Specifically, they unfold over time and in a nonlinear fashion, which is consistent with a nonlinear developmental cascade that accelerates and then decelerates as the process of prisonization unfolds. While those mid-twentieth century studies (Wheeler, 1961; Glaser & Stratton, 1961; Garabedian, 1963; Wellford, 1967) examined prisonization and how it shapes attitudes over time, as opposed to social interactions and how they shape behavior over time, their results and the interpretations thereof are both relevant and instructive for the simple reason that social interactions with other inmates, particularly cellmates, are the primary means through which Clemmer (1940, 1950) theorized prisonization would occur.

Prisonization and prison peer effects. As Glaser and Stratton (1961) and Wellford (1967) presaged, current conceptualizations of social interaction effects refer to their constituent contextual, selection, and simultaneity effects and expect the shared social context to contribute to socialization processes (e.g., Jussim & Osgood, 1989; Manski, 1993; Hartup, 2005; Mouw, 2006; McGloin, 2009; Durlauf & Ioannides, 2010; Sacerdote, 2014). In the current study, the shared prison environment contributes to prisonization processes that operate primarily through social interactions between inmates who bring their own pre-prison proclivities to those interactions (Clemmer, 1940; Wellford, 1967). In addition, prior prisonization studies highlighted the potential importance of the duration of exposure to the prison environment and, specifically, to the other people in it.

By today's standards of longer prison sentences (Blumstein & Beck, 1999; Raphael & Stoll, 2009; NRC, 2014), the prison sentences and time periods examined by Wheeler (1961), Wellford (1967), and Garabedian (1963) were short, but nevertheless comparable to those of the first-time releasees from PADOC who served just over two years on average, but who may have served up to seven years. Wheeler (1961) examined inmates (n=204) serving, on average, three-year sentences who had not yet been incarcerated for six months, those who had been incarcerated for at least six months, but who had more than six months left to serve, and those who had less than six months left to serve. Garabedian (1963) followed Wheeler's (1961) early, middle, and late operationalization in his examination of 335 inmates, whose sentence lengths he did not report. Wellford (1967) also examined inmates (n=120) in early, middle and late phases of their up to six-year prison stays, but chose to delimit the early and late phases at nine, rather than six, months after admit and prior to release.

Each of those studies found that, on average, inmates in the middle phase were more prisonized in that they, on average, revealed higher preferences for antisocial behavior and lower preferences for prosocial behavior than inmates in the early (within six or nine months of commitment) or late (within six or nine months of release) phases. [3] Thus, on average, evidence of prisonization took some time (at least six months) to emerge and appeared to dissipate as an inmate's release date approached but, as predicted by Clemmer (1940, 1950), inmates appeared more antisocial upon exiting prison than they did upon entering it. Based on the sentence lengths, the zenith of that parabola is likely to have occurred near the middle of inmates' prison stays, so at approximate average of one and a half to two years for both samples, as only 29 men in Wellford's (1967) sample served more than four years. [4]

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[3] Wheeler (1961, p. 709) reported variation in prisonization patterns, as does Garabedian (1963), who attributes this variation to social types (e.g., Wellford, 1967).

[4] In later work that was also cross-sectional, Wellford (1973) found no evidence of this U-shaped curve. He suggested that a longitudinal analysis, such as the one undertaken in the current study, would better serve to evaluate the prisonization process.

As noted by Wheeler (1961, p. 709), each of these studies is similarly limited in that it employed a cross-sectional design. Inmates were not followed longitudinally to see if their individual prisonization trajectories followed the same parabolic pattern observed cross-sectionally (Wellford, 1973). Each is also limited in that the responses of inmates were taken at face value: the authors did not consider that the effects they attributed to anticipatory socialization may have, in part, been representative of inmates' desire to appear (rather that actually be) less prisonized near their release dates, so as not to impact their potential for release (Glaser & Stratton, 1961; Wellford, 1973).

Despite their shortcomings, the prior prisonization studies suggest that the evolution of inmate relationships may help to explain the degree to which inmates exhibit prisonization with respect to time served. In particular, the timing of the most stable cellmate relationships (i.e., those that last the longest amount of time) suggests that these longest-duration associations may help to explain the trajectory of the prisonization process over time.

According to the prior prisonization studies, PADOC inmates should not become maximally prisonized before six or nine months in prison, which is about when (at ten months, on average) they enter into their most stable, longest-duration cellmate association. As detailed in Chapter 5, upon entry into the prison system, PADOC inmates spend about three months in initial classification, then another three to nine months cycling through cellmates in their assigned facility before finally settling on a cellmate with whom they spend the most time (approximately six months) during their slightly more than two-year average prison stays. As their most stable associations develop and dissolve, on average, somewhere near one and a half to two years after the releasees' commit dates, the PADOC releasees may become maximally prisonized as a result of the ongoing influence of their longest-duration cellmate. Given that the releasees are first-timers, the trend toward acquisition of antisocial attitudes and behaviors may occur because they are celled with more criminally experienced cellmates, as argued above. The continued adoption of antisocial attitudes and behaviors may also diminish as releasees become more congruent with their cellmates over time, as suggested by balance theory (Heider, 1958; McGloin, 2009). Nevertheless, the first-time releasees should, on average, exit prison evincing higher degrees of criminality than when they entered (Clemmer, 1950; Wheeler, 1961).

The potential emergence and subsidence of prison peer effects. The temporal dependence of prisonization may be mirrored in a temporal dependence of prison peer effects. After some period of adjustment to their cellmates, releasees may experience the most intense prison peer effects. Before that period, evidence of social influence may not be detectable because the cellmate relationship is burgeoning. After a period of development during which prison peer effects might become and stay detectable, the eventual congruence between the behavior and attitudes of the releasee and his cellmate, which is predicted by balance theory, implies that evidence of social influence will again become undetectable. That cellmates reach a point in their relationship at which there is little associational conflict to resolve and at which once detectable prison peer effects become undetectable was suggested by Clemmer (1940) who observed that "there is not much talk between men who have been in a cell for some time [because within] a few months they have told each other as much of their life histories as they wish to" (p. 102). Therefore, evidence of the transmission of antisocial values via cellmate associations may, like prisonization itself, follow a parabolic trajectory through time, as the relational distance between a releasee and his cellmate closes.

Peer effects in prison may take some time to emerge partially because social relationships take time to develop. That social interaction effects may take some time to emerge is typically not considered in the literature that examines social interactions. This is most likely because the social relationships typically studied are established relationships, including those between friends, romantic partners, and classmates. Moreover, even if the studied relationships are not already established, the impetus for them to form (i.e., homophily or common interest), is generally implicitly assumed to stimulate immediate or near-immediate social interaction effects (Hartup, 2005).

In the prison context the assumptions that social relationships among inmates are preexisting, ongoing, or predicated on intimacy, affection, or even a shared desire to share space with each other clearly cannot be made. Prison inmates, particularly first-time inmates, are systematically celled together without their consent. Moreover, although PADOC inmates can select into cellmate associations, they might select into those associations for reasons ancillary to the characteristics of potential cellmates. For example, as discussed in Chapter 5, inmates may end up with cellmates based on a desired cell location or the availability of a bottom bunk (personal communication, 2013). Thus, while inmate associations could be predicated on the similar characteristics, shared interests, or emotional ties that are assumed to generate social interaction effects in other contexts, they cannot be assumed to be (Clemmer, 1940, p. 104-5; Earley, 2000). Nor, therefore, can cellmate relationships be assumed to immediately engender prison peer effects.

The inability to make assumptions about the impetus for and nature of cellmate associations highlights the role of duration as something more than a simple modality or moderator of associations in the prison context. Specifically, as associations develop and dissolve there may be distinct durations of association wherein social interaction effects are detectable and those wherein they are not. Evidence of prison peer effects stemming from inmate interactions may take some time to become detectable. Moreover, they may subside, once again becoming undetectable as inmates anticipate their withdrawal from those associations due to their impending release (Glaser & Stratton, 1961) or an impending cell move, which might be due to a cellmate's impending release or transfer (e.g., Earley, 2000). Alternatively, congruency between cellmate attitudes and behaviors may be achieved or nearly achieved after some time, which suggests that social interaction effects are detectable only when there is ongoing incongruence in the association (Clemmer, 1940; Heider, 1958; Jones & Schmid, 2000; McGloin, 2009). The duration of cellmate association, therefore, needs to be examined, not solely as a moderator, but as a potential delimiter of where in the context of the duration of these particular social relationships social interaction effects may be evident.

The potential for prison peer effects to persist long enough to account for prison effects. If prison peer effects are to account for a portion of the null or criminogenic prison effect, they must persist for at least as long as long as the standard follow-up period in the literature that examines post-incarceration reoffending and reports prison effects. Three to five year follow-up periods are standard in the incarceration and reoffending literature (Langan & Levin, 2002; Helland & Tabarrok, 2007; Nagin et al., 2009; Nieuwbeerta et al., 2009; Nagin & Snodgrass, 2013; Durose et al., 2014). To accord with that literature, the prevalence of reoffending is to be measured at four years post release.

It is consistent with the broader peer literature to expect social interactions to impact temporally distant outcomes well within the range of four years. Many studies of peer influence that use the AddHealth data, for example, exemplify the implicit (i.e., atheoretical) expectation that peer effects can persist for many years. Wave I of the AddHealth study occurred in 1995, Wave II in 1996, Wave III in 2001, and Wave IV in 2008. Studies have attributed peer influences in Wave II to Wave III outcomes (a temporal distance of five years) and peer influences in Wave III to outcomes in Wave IV (a seven-year difference). Those studies examine temporally and contextually distal outcomes attributable to peer influence as diverse as fertility (Balbo & Barban, 2014), human capital acquisition (Babcock, 2008), suicide (Abrutyn & Mueller, 2014), and substance use (Ali & Dwyer, 2009). It is, thus, consistent with the empirical literature on social interactions to expect peer effects to persist over time.

It is also consistent with the, albeit scant, empirical evidence related to prisonization to expect prison peer effects to persist. Wheeler's (1961) prisonization study provides some evidence that prison peer effects endure. As Clemmer (1950) predicted, Wheeler (1961) found that inmates who had previously been incarcerated were, on average, more prisonized than first-time inmates at the same stage in their current spell of incarceration. This suggests that the effects of prisonization, which operate through social influence, may linger.

The cascading potential of prison peer effects. Developmental cascades can support the argument that prison peer effects persist while simultaneously accounting for

Wheeler's (1961) finding that prisonization is a nonlinear process. One of many possible developmental pathways that might account for the persistence of cellmate social interaction effects over a period of several years, during which many social interactions subsequent to the cellmate (i.e., prison peer) interaction occur, is that social interactions that take place between cellmates in prison can generate spillover effects (i.e., cascades), which influence the outcomes of prison releasees as they reenter society (Masten et al., 2005; Masten & Cicchetti, 2010; Krohn et al., 2011).

If a social interaction with a cellmate exerts causal influence on reoffending outcomes, all subsequent social interactions, plus any other outcomes intermediate to reoffending, can be viewed as emanating from that single cellmate interaction (e.g., Lorenz, 1972; Sherman & Harris, 2013). This principle underlies cascade theory, a popularized example of which is the well-known butterfly effect, which attributes a tornado in Texas to the flap of a butterfly's wings in Brazil (Lorenz, 1972). It also underlies the logic of Sherman and Harris's (2013) explanation of their finding that a single arrest of a suspect for domestic violence could negatively impact the mortality of their victims more than twenty year later: transient experiences, both positive and negative, can have long-lasting consequences. In the current context of prison peer effects, the argument being made is that prison peer effects can impact post-prison social relationships and behaviors.

To make this argument more concrete in the context of social interactions that occur during incarceration, an hypothetical cascading model of the persistence of prison peer effects can be adapted from Dishion et al.'s (2010) model of problem behavior amplification. Dishion et al. (2010, p. 606) developed a peer dynamics cascade model whereby childhood problem behavior leads to social and academic failure at ages 11 and 12, which facilitates gang involvement (i.e., deviant peer association) at ages 13 to 14, through which deviancy training at ages 16 to 17 operates to engender violent behavior in early adulthood when young adults are aged 18 to 19 and entering the transition to adulthood. With respect to timing, note that the deviant peer associations observed by Dishion et al. (2010) occurred five years before the observed violent behavior, whereas the prison peer associations to be observed in the current study occurred, on average, at about the same temporal distance.

A cascade model can explain how prison peer effects might generate lasting criminogenic effects for the members of the PADOC first-time release cohort who entered into the prison system, encountered and remained with a particular cellmate, and thereafter continued along a path to increased reoffending that would not have been followed, were it not for the social interaction with that cellmate. That hypothetical developmental pathway might be: criminal behavior leads to imprisonment, which necessitates living with a cellmate. Via learning mechanisms, particularly deviancy or criminality talk, social interactions with that cellmate increase prisonization, which engenders continued criminal behavior when the more prisonized inmate is released because that inmate's attitudinal shift toward more criminality influences each of his subsequent interactions (Clemmer, 1940, 1950). Thus, like peer effects that result from deviant peer interactions can be theorized to endure over a period of many years and through shifting social and developmental landscapes, so can prison peer effects due to cellmate associations be theorized to persist over lengthy time periods, during which other associations may occur. In short, prison peer effects on reoffending can be attributed to prior peer interactions, per cascading processes (Sutherland, 1947; Lorenz, 1972; Masten et al., 2005; Cunha et al., 2006; Cunha & Heckman, 2008, 2010; Dishion et al., 2010; Sherman & Harris, 2013).

While cascading processes can explain the persistence of prison peer effects over many years in the post-prison domain, it is important to re-emphasize that the current study is not testing developmental cascade theory or the criminological learning theories, such as differential association and balance theories, which are consistent with the application of cascade theory. In the current study, the object is to determine whether prison peer effects can account for prison effects that have emerged at a four-year follow-up. Developmental cascades have been discussed solely as a potential justification for why prison peer effects can be expected to persist for four years, not as a theory of that persistence that is to be tested via the current analysis.

Prison peer criminal experience and criminality metrics. Once it is determined where in time to look for prison peer effects with respect to their onset and persistence, those effects can be identified by examining interactions between the criminality of the releasees and the criminality their cellmates, as indicated by their criminal experience and their assessed potential to commit new crimes inside and outside the prison context. In the prison context, criminal experience and criminality can be indicated through multiple measures. Those measures include, but are not limited to, prior incarceration, prior arrest, and risk of recidivism and misconduct. While these measures have weaknesses in that they fail to directly capture attitudes (Matsueda, 1988), behaviors such as these have routinely been used to indicate attitudes and may better capture differential associations even if they do not truly measure them (Warr & Stafford, 1991).

Cellmates with prior incarcerations should be more criminogenic and generate more criminogenic effects on releasees than cellmates who do not. As previously discussed, this may be because they hold more criminal attitudes and have acquired more criminal skills, because they are more criminally connected, or because they garner more respect or prestige in the prison environment. The adoption of differentially more serious criminal behaviors and attitudes is revealed by differentially more serious behavior. For similar reasons, cellmates with more arrests are likelier than cellmates with fewer arrests to generate criminogenic effects because they are likelier to commit more offenses themselves (Sutherland, 1947; Clemmer, 1950; McCarthy & Hagan, 2001; Mears et al., 2013; Skarbek, 2014). The notion that some inmates are likelier to recidivate or misbehave in prison is reflected in actuarial risk assessment tools that are routinely used to classify offenders in terms of their need for services, their potential to commit future crimes inside and outside prison (Feeley & Simon, 1992; Kleiman, Ostrom, & Cheesman, 2007; Monahan & Skeem, 2013; Starr, 2014). As such, they reflect, although they cannot perfectly measure, criminality. The process of constructing a risk score measure that reflects the measurement of criminality in the Pennsylvania Department of Corrections is described more fully in Chapters 4 and 6.

Direct and Indirect Evidence of Prison Peer Effects

> *"… [E]xcept for the inmates purposefully ostracized by other inmates, even the "ungrouped" inmates are seldom isolated. They do associate with other inmates---cell mates, work companions, recreation team mates, eating partners, and so forth…" (Sutherland & Cressey, 1955, p. 503).*

Although it is clear that social interactions among inmates have been cause for concern for nearly two centuries, only a handful of prior studies have examined peer effects in incarcerative environments. As was described above, Drago and Galbiati (2011) estimated prison peer effects by exploiting a unique policy event in Italy that reduced overcrowding in Italian prisons by releasing inmates early, with the caveat that the remainder of their sentence would be served if they recidivated. The social interaction effects they estimated suggest that inmates with peers who have longer residual sentences recidivate less. Those indirect peer effects were as large as the direct effect of own residual sentence on recidivism.[5]

Bayer et al. (2009) and Ouss (2011) estimated prison peer effects directly. Unlike Drago and Galbiati (2011), they did not rely on a non-reoccurring policy shift (i.e., an instrumental variable) to gain causal inference. Bayer et al. (2009) exploited exogenous variation in peer group composition relative to the date of admission to facilities to estimate peer effects at the facility level for juveniles in Florida (e.g., Hoxby, 2000). They found no evidence that juveniles appear to be learning new crimes as a result of social interactions. They did, however, find small reinforcing effects for some crimes. When juveniles convicted of burglary, larceny, assault, drug, and sex offenses shared a facility with similar offenders, they were more likely to reoffend with the same crime. The Ouss (2011) study estimated social interaction effects resulting from dormitory assignments. The preliminary results from her unpublished study of short-term stay

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[5] Note that inmates with longer residual sentences were not necessarily more serious offenders. That some inmates had longer residual sentences implies only that, at the time of the Collective Clemency Bill, the inmates with the longer residuals had served lesser portions of their sentences. Releasees with peers who had more unserved (i.e., residual) time were deterred more than releasees with peers with less unserved time. The peer effect estimated by Drago and Galbiati (2011), therefore, reflects evidence of a deterrent effect of punishment that somehow spilled over from peers. It does not reflect the counterintuitive interpretation that the influence of deviant peers led to less recidivism on the part of releasees.

facilities in France concurred with the Bayer et al. (2009) findings in that they indicated that reinforcing effects for some crimes, notably theft and drugs.

Who are Prison Peers?

The prior prison peer effect literature examined direct prison peer effects for groups of inmates. The Bayer et al. (2009) study measured peer effects at the facility level. Similarly, Lerman (2009) attributed her findings to peer effects at the facility level. Wellford (1973) and Gold and Osgood (1992) found that more proximal associations matter more. Wellford (1973) examined social interactions at the "cottage" or cellblock-equivalent level, whereas Gold and Osgood (1992) found that prison peer effects are determined and most likely to operate at the cellmate level, as predicted by Clemmer (1940, 1950).

Despite this prior research that focused on groups of inmates, there are conceptual reasons to begin an analysis of prison peer effects at the dyadic cellmate level. In testing her balance theory, McGloin (2009) used data on best friends in the AddHealth (Harris et al., 2009) data set. She argued that focusing on best friend dyads, rather than a peer group was, "a particularly reasonable decision because Heider's conception of balance discussed an individual actor and his/her relationship with two objects (i.e., another person and an idea/belief/etc.)…and it is wise to first establish whether a relationship exists at this dyadic level before moving to larger contexts" (p. 451). Her guidance, in combination with the insight of Clemmer (1940, 1950) and Gold and Osgood (1992), is taken in the current study: dyadic releasee-cellmate pairs are examined for their potential to exert criminogenic effects.

The decision to examine prison peer effects between paired cellmates is appropriate for several reasons. First, this is an initial investigation into the potential for cellmates to generate prison peer effects, so it is prudent to follow McGloin (2009) in examining core dyadic associations before evaluating larger groups. Gold and Osgood's (1992) observation that cellmates are the likeliest locus of prison peer influence further supports the decision to examine inmate pairs. Finally, adopting a dyadic framework comports with the contextual structure of the prison system.

The primary structural relationship in the prison context is between an inmate and his cellmate. The vast majority, more than 90%, of PADOC prison beds are housed in double cells, which means that the majority of PADOC inmates live in a cell with one other inmate. Naturally, however, inmates share cells with more than one cellmate during their prison stays.

Criminological theory points to a single cellmate most likely to generate peer effects: the cellmate with whom the releasee spent the most time. Sutherland (1947) expected duration to moderate the effect of deviant peers. Clemmer (1950) similarly expected that prisonization would increase with time spent in association with other inmates. Several empirical investigations have confirmed these expectations (Wheeler, 1961; Agnew, 1991; Warr, 1993; Haynie et al., 2005), so it is reasonable to expect that the cellmates who spend the most time with each other will exert detectable prison peer effects, even if it is also possible that the effect of that cellmate will decrease after increasing (Wheeler, 1961).

The PADOC data include up to the minute information on the duration of cellmate associations. Variation in the duration of the longest cellmate relationship can be explored to see if it moderates prison peer effects due to criminogenic cellmates and to determine whether those effects are ever-increasing, subject to diminishing marginal returns, or parabolic. Specifically, the longest-duration cellmate associations provide the widest range over which to explore when prison peer effects might emerge, how they might evolve, and whether and when they might subside and, potentially, become undetectable over the course of a cellmate association.

From the data it is clear that the release cohort spent more time celled with some cellmates than they did with others; considerably more time, in fact. The PADOC releasees spent an average of 29 (SD=41) days with each of their cellmates, but an average of 182 (SD=144) days, or about one-quarter of their time in prison, with their longest-duration cellmates. Moreover, each releasee celled with ten cellmates on average before finally settling into this stable, longest-duration association. Twenty-five percent of the releasees remained in their most time-intense association until they were released.

Duration of cellmate association information can be used to differentiate stable cellmate associations from unstable ones and to explore variation within those stable associations. While the eventual stability of some cellmate associations may be contextually induced in that correctional officers may disallow cell moves, stability nonetheless differentiates a releasee's most stable cellmate association from his associations with each of his other cellmates because the most stable association persists for a longer period of time. The implications of that persistence can be explored in the current study, as can its relationship to less stable cellmates.

Whether single social actors, such as best friends, or broader peer groups are more likely to be socially influential is an unresolved issue in the peer literature (Hartup, 2005;

Payne & Cornwell, 2007; An, 2011; Rees & Pogarsky, 2011). This is even truer in the prison context where, as Sutherland and Cressey (1955) noted, social interactions between inmates have rarely been studied. In the current study, dyadic relationships between cellmates are of primary interest due to the dyadic structure of the prison environment and for the reasons articulated by McGloin (2009) and Gold and Osgood (1992). Of secondary interest is how the effects of dyadic associations on reoffending compare to the effects of prison peer groups on reoffending (e.g., Rees & Pogarsky, 2011). To make those comparisons, each of the cellmates with whom an inmate shared a double cell can be identified, so prison peer group (i.e., primary group or reference group) effects can be controlled and their contribution to prison peer effects can be estimated via the analytic framework described in Chapter 3.[6]

In Summary

To explore one reason why incarceration might increase reoffending, the current study attempts to demonstrate that persistent prison peer effects are a real, detectable, and measurable phenomenon among first-time releasees from the Pennsylvania Department of Corrections. The preceding discussion identified a key means through which prison peer effects might operate: differential association with more criminally experienced or criminally able individuals may foment criminal behavior. That discussion also highlighted the potential importance of the duration of cellmate associations in producing that behavior.

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[6] Prison peer groups may also extend beyond cellmates. Section (i.e., unit) level effects also have the potential to be controlled although, as described in Chapter 8, they could not in the current study because the sample sizes associated with the sections in the dyadic data were too small.

Duration and prisonization are implicitly connected because inmates are sentenced primarily with respect to time and because prisonization is theorized to operate through interaction with cellmates. However, the duration of association may affect individuals differently in the prison context than in the non-prison context. In the prison context, social interaction effects may evolve, take some time to emerge as inmates assimilate into the prison environment, grow as their relationships with each other develop, and dissipate as they anticipate their reentry back into the community. Cellmates, in particular, cannot be assumed to have had prior relationships or to have connected emotionally. Therefore, there is a need to determine how long inmates might need to interact with each other to generate detectable prison peer effects.

The choices to examine the outcomes of a first-time release cohort and a longest duration cellmate create a strong framework in which to detect and explore the evolution of prison peer effects. First-timers are untainted by prior experiences with incarceration that are hypothesized to increase criminality (Clemmer, 1950; Wheeler, 1961; Jones & Schmid, 2000; Nieuwbeerta et al., 2009). Moreover, even if inmates "become somewhat more conforming to conventional norms" upon their return to the community (Glaser & Stratton, 1961, p. 388), Wheeler (1961) showed that returning inmates have higher levels of criminality than do first-timers.

Within a dyadic relationship, the longest duration cellmates provide the widest range of time over which to explore the onset of and shifts in prison peer effects as cellmate associations unfold over time. An inmate's most stable cellmate association is, of course, situated in the context of a broader prison stay. While the timing of the initiation of this association generally comports with timing of the onset of prisonization effects, the effects of that association may be dependent on the amount of time a releasee expects to be in prison after that relationship is initiated (Wheeler, 1961; Glaser & Stratton, 1961; Wellford, 1967). As discussed in Chapter 6, this element of a releasee's prison stay can also be deduced.

Unfortunately, for reasons that will be described in more detail in Chapters 4 and 6, adjudicating between the different potential theories of social influence (i.e., prisonization) and the different potential mechanisms through which social influence might counteract specific deterrence in the prison environment is both beyond the scope of this study and beyond the support of the unique cellmate assembled dataset. If effects on reoffending proceeding from social interactions with other inmates are detected, this study cannot and will not determine how they were generated. The mechanisms of social influence, including whether or not developmental cascades can account for the persistence, acceleration, or deceleration or prison peer effects, will remain elusive. Nevertheless, this study makes a valuable existential contribution that must precede the expositional step that future work will take: it attempts to detect causal prison peer effects.

Only if prison peer effects on four-year reoffending outcomes are shown to exist will they need to be explained. If persistent prison peer effects are shown to exist, the current study will serve as fodder for a second step through which the mechanisms of social influence among cellmates can be explored with the goal of better understanding the etiology of prison peer effects. Therefore, while any prison peer effects detected by this study will be interpreted in the context of theoretical framework outlined in the current chapter, it should be recognized that those interpretations are merely hypothetical narratives intended to contextualize and clarify the results of the analyses.

The next chapter details the difficulties of estimating social interaction effects, more generally, and then describes how current statistical methodology based on economic theory can overcome those difficulties to estimate prison peer effects. Chapter 4 overviews the synthesis of the criminological theory discussed in this chapter and statistical methodology discussed in Chapter 3 into an operational framework that respects the limitations of the data and characterizes the process through which inmates become cellmates and, hypothetically, generate prison peer effects.

CHAPTER 3: The Need for Methodological Innovation to Estimate Prison Peer Effects

There is clear theoretical and empirical motivation for asking whether social interactions amongst prison inmates increase their propensity to reoffend (Clemmer, 1940; Sutherland & Cressey, 1955; Bayer et al., 2009). In particular, there is reason to assume that criminogenic prison peer effects emerge after a releasee interacts with a cellmate who has more criminal experience than he does. Moreover, those effects are expected to take some time to emerge as inmates who are celled together acclimate to each other and to vary based on how much time inmates ultimately spend with each other. This study seeks to causally identify the effects of prison peer interactions on reoffending, without seeking to explain the mechanisms that drive those effects.

Causal identification of social interaction effects is a substantial estimation problem that is endemic to the social sciences. This chapter reviews the challenges of causal identification of social interaction effects and introduces a new methodological framework, local instrumental variables (Heckman & Vytlacil, 1999, 2005), which has the potential to help researchers interested in social interaction effects to overcome some of those challenges.

Estimation of Causal Social Interaction Effects

Nichols (2007, p. 507) writes, "[E]stimating…[a] 'treatment effect' is the goal of much research, even much research that carefully states all findings in terms of associations rather than causal effects." With its focus on establishing whether social influence causes criminal behavior, the vast majority of criminological research on social interaction or peer effects falls squarely into that category (for reviews see Warr, 2002;

Pratt et al., 2010). However, careful attention to the conditions under which causality can be established in observational studies has often been lacking in the criminological literature (Hirschi & Gottfredson, 2000; Bushway & Apel, 2010; Loughran & Mulvey, 2010). This is particularly true in the peer effects literature wherein authors make statements such as, "we believe our statistical controls for selection are at least as strong as those in any previous research on peer effects for delinquency" (Haynie & Osgood, 2005, p. 1119). Such statements want for both proof and precision. Thus, what has been established, over and over again, is that there is a clear correlation between the behavior and characteristics of people and the behavior and characteristics of their peers (Glueck & Glueck, 1950; McPherson, Smith, & Cook, 2001; Warr, 2002; Weerman, & Smeenk, 2005; Mouw, 2006; Pratt et al., 2010).

Whether social interaction effects can be causally implicated in the behavior of individuals remains a contentious issue across disciplines (McPherson et al., 2001; Hartup, 2005; Mouw, 2006; Gangl, 2010; An, 2011; Angrist, 2013; Sacerdote, 2014). For example, Angrist (2013) asserted that "the recent empirical work implementing robust peer effects research designs…has uncovered little in the way of causal effects" (p. 21). Similarly, Osgood and Briddell (2006, p. 160) concluded that "deviant peer influence is not as potent a force as some have argued." More circumspectly, Sacerdote (2014) observed that context appears to moderate estimates of social interaction effects greatly (e.g., Hartup, 2005), which calls into question the generalizability of peer effects estimated in one context to any other context (Horney, Tolan, & Weisburd, 2012). However, he ultimately concurred with Osgood and Briddell (2006), who succinctly summarized that "peer influence is genuine, but modest" (p. 160).

Nearly since the inception of modern criminological thought, criminologists have been similarly preoccupied with the debate over whether social influence matters in the production of reoffending. That debate pits static (or population heterogeneity or ontogenetic) arguments against dynamic (or state dependence or sociogenetic) arguments (Paternoster et al., 1997; Thornberry et al., 2012). The former, of which Gottfredson and Hirschi (1990) are the primary modern advocates, denies social influence and adopts the position of Glueck and Glueck (1950) who famously noted that "birds of a feather flock together" (p. 164). In contrast, proponents of the latter argue that social influence is a major avenue through which criminality develops (Sampson & Laub, 1993, 2003; Akers, 2009; Thornberry & Krohn, 2005). This debate has persisted largely because definitively demonstrating that estimated peer effects are not selection artifacts is extremely difficult (Hirschi & Gottfredson, 2000; Manski, 1993; An, 2011; Angrist, 2013).

Manski (1993) formally described the difficulties associated with identification social interactions effects. At its core, the problem is one of disentangling a "peer effect" from confounding effects due to simultaneity (i.e., "the reflection problem," to which the title of his article refers), selection (i.e., the "birds of a feather" or the tendency toward homophily that human relationships display), and the contextual effects generated by the shared social environment. A peer or social interaction effect is an effect, isolated from the aforementioned confounding effects, exerted on an individual under study by other individuals with whom the studied individual interacts (Jussim & Osgood, 1989: Mouw, 2006). Typically, a peer effect is evidenced by some measurable change in behavior, but it could also be a measured change in attitudes or beliefs or opportunities (Matsueda, 1988, 1992; Warr & Stafford, 1991; Osgood, Wilson, O'Malley, Bachman, & Johnston, 1996; Warr, 2002; Pratt et al., 2010).

In the present study, the members of a first-time release cohort from the Pennsylvania Department of Corrections are the individuals under study and their cellmates are their peers. The cellmates are expected to exert an effect on the reoffending outcomes of the releasees through social influence. Only the prison peer effects can be detected: the mechanisms through which prison peer influence operates can be inferred but not demonstrated or tested.

Overcoming the bias associated with each of the potential confounders of peer effects is a considerable task. As described by Spelman (2008) and Nagin et al. (2009), simultaneity plagues the incarceration and reoffending literature. Fortunately, in the context of this study, the reflection problem is not a problem because, while it is context-dependent, there is a clear temporal order associated with the potential for incarceration to impact reoffending: social interactions that occur in the prison context are expected to affect criminal behavior in the post-prison context, several years after the social interactions have taken place.

Social interactions that occur in one context have previously been shown to affect later outcomes in another, wholly disparate, context. For example, high school peer interactions have been shown to impact academic achievement in college and social interactions in college have been shown to impact post-graduation employment (Fletcher & Tienda, 2010; Bifulco, Fletcher, & Ross, 2011). In the current study, the cellmate social interactions expected to generate prison peer effects take place within prison, but the reoffending outcomes are observed after those social interactions have ended. The construction of the problem, therefore, eliminates simultaneity bias. Selection bias, however, certainly remains.

The social interactions literature, particularly in economics, provides some guidance with regard to statistical means of overcoming selection bias. Cellmates are akin to college roommates, who have been studied extensively in the domain of social interaction effects. In his seminal college roommate study, Sacerdote (2001) demonstrated that Dartmouth College roommates were assigned randomly, after five characteristics (gender, smoking, cleanliness, study, and sleep habits) were taken into account. This pseudo-randomization of roommates into pairs overcomes the selection problem (Sacerdote, 2001; Zimmerman, 2003; Stinebrickner & Stinebrickner, 2006).

Like college roommates, cellmates appear to be pseudo-randomly assigned to share living space in the PADOC prison context. As described in Chapter 5, initial assignment to a cell is contingent mainly upon race and medical limitations, with age playing a secondary role. However, the current study does not need to solely rely on assumptions regarding pseudo-randomization for identification. The first cell assignment can still be leveraged, but additional exclusion restrictions or instrumental variables can be identified (Imbens & Angrist, 1994). Those potential exclusion restrictions include characteristics of the cell environment and the timing of the placement with respect to the cellmate's prison stay. In a two-stage framework, valid exclusion restrictions eliminate selection biases due to unobserved heterogeneity or omitted variables because they difference out the levels of the covariates in order to identify gains from treatment, as described below (Heckman, 1976; Imbens & Angrist, 1994; Bushway & Apel, 2010).

The exclusion restrictions employed in the current study will be described, conceptually defended, and empirically validated in Chapter 8.

Even if pseudo-random assignment and exclusion restrictions address selection biases in the current identification problem, there remains the problem of common social environments. Actors in the same social environment are subject to the same contextual effects, which can bias effect estimates (Manski, 1993; Fletcher, 2009, 2012; Durlauf & Ioannides, 2010; Horney et al., 2012; Aliprantis, 2013; Sacerdote, 2014).

> *"In our view, unobserved group effects represent the most difficult hurdle to the construction of persuasive evidence of social interactions because, unlike self-selection, there is typically no economic reasoning to facilitate modeling the influences" (Durlauf & Ioannides, 2010).*

As Durlauf and Ioannides (2010) suggested, ideal solutions to the problem of empirically handling contextual effects are in short supply. Fletcher (2009) argued that instrumental variables (i.e., exclusion restrictions) in concert with contextual fixed effects can identify social interaction effects. He presented evidence that suggests that studies of social interactions that did not use instrumental variables in concert with contextual fixed effects likely overstated the magnitude of the influence of social interactions. Angrist (2013) made a similar argument. He described a model wherein an individual's probability of being treated or not is determined by the saturation of treatment in a particular context (e.g., an individual's probability of receiving job training depends on the capacity of the local job training center). In that situation, the contextual effect equals the average treatment effect and any discrepancy between the contextual and average treatment effects equates to a peer effect (Moffitt, 2001; Angrist, 2013; Crepon, Duflo, Gurgand, Rathelot, & Zamora, 2013).

While innovative, Fletcher's (2009, 2012) solution and others like it (e.g., Moffitt, 2001; Angrist, 2013) do not address the recent literature that demonstrates the fragility of the instrumental variables method with respect to the real-world situation where individuals' decisions are affected by the unobserved outcomes they expect as well as by their unobserved characteristics (Manski, 2005; Heckman & Vytlacil, 2005; Heckman, Urzua, & Vytlacil, 2006). Heckman and his colleagues call this situation *essential heterogeneity*.

Causal Inference and Essential Heterogeneity[7]

When subject to the same treatments, individuals who are observationally equivalent from the perspective of researchers have routinely been shown to display heterogeneous outcomes, including those related to various criminal behaviors (e.g., Heckman, 2001; Laub & Sampson, 2003; Manski, 2005; Heckman & Vytlacil, 2005; Loughran & Mulvey, 2010). This phenomenon, which is known as response heterogeneity, is generally attributed to selection on levels, or differences in the unobserved characteristics of the individuals being evaluated, and their environment. However, response heterogeneity may also be attributable to selection on gains or choices made based on the unobserved and imperfect information individuals have about the potential benefits and detriments of their treatment options (Heckman et al., 2006).

Essential heterogeneity. Heckman et al. (2006) coined the term essential heterogeneity to refer to the response heterogeneity in outcomes that arises as a result of

[7] The non-technical discussion in this section borrows heavily from Heckman and Vytlacil (2005) and Heckman, Urzua, and Vytlacil (2006). The reader is referred to those pieces for technical proofs of the statements made herein. For a more accessible implementation, see Basu, Heckman, Navarro, and Urzua (2007).

some combination of selection on gains and selection on levels. Selection on levels, which is also called selection bias, omitted variables bias, or unobserved heterogeneity, is a kind of information asymmetry: individuals make treatment decisions based on information that researchers do not have about those individuals, their environment, and the treatment (e.g., peers, cellmates) itself. In the case of social interactions in prison, information researchers do not have about the treatment decision might include personality characteristics and behaviors that inmates use when selecting their cellmates or that correctional officers use when assigning inmates to cells (i.e., celling inmates); information that also plays a role in inmates' post-prison decisions to commit crime.

Particularly relevant to criminology is the unobserved characteristic of criminal propensity or criminality. In criminology, criminality is often equated with self-control or a high discount rate (Gottfredson & Hirschi, 1990; Bushway, Piquero, Broidy, Cauffman, & Mazerolle, 2001; Nagin & Pogarsky, 2001; Hirschi, 2004), but differential association theory adopts a broader perspective of criminality wherein the accumulation of criminal attitudes, beliefs, definitions, and rationalizations inspire criminal behavior. As such, criminal behavior often serves as a proxy for criminality in criminological studies (Warr, 2002; Pratt et al., 2010). Since Matsueda's (1988) criticism of the practice of using criminal behavior as a proxy for criminal attitudes, eliciting information about criminal propensity has consumed much of the criminological literature related to differential association and social learning theories more generally (Pratt et al., 2010). Necessarily, however, criminal propensity remains unobserved, either in part or in whole, and either because it is unmeasured or because it cannot be completely measured (e.g., Matsueda, 1988; Duckworth, Tsukayama, & Kirby, 2013). Unobserved criminality is theorized to influence outcomes indirectly through the intermediate decisions that also contribute to those outcomes (i.e., selection on levels) and also directly through selection on gains.

Selection on gains refers to the potential for individuals to have information about the expected outcomes of treatment (e.g., enhance crime committing capabilities), as opposed to the treatment itself (e.g., characteristics of cellmates), upon which they base their treatment decisions. In education, for example, selection on gains can arise when individuals forego current earnings and select into more education (i.e., college) in the hopes of earning higher wages when that educational process completes. Selection on gains can also happen in the production of criminal behavior in prisons. This is exactly the learning mechanism that "schools of crime" proponents postulate about the relationships formed between prison inmates: inmates select into cellmate relationships based on what they can learn from those cellmates about criminal opportunities and methods (e.g., Bentham, 1830; Clemmer, 1950; Nagin et al., 2009).

Prior approaches to causal inference under response heterogeneity. Heckman and Vytlacil (2005) describe two main approaches that have been used to estimate treatment effects, a structural approach and a treatment effect approach. Both have been used to estimate social interaction effects (e.g., Warr, 1993; 1998; Haynie & Osgood, 2005; Hoxby & Weingarth, 2005; Payne & Cornwell, 2007; Fletcher, 2009, 2012). Structural approaches only rarely address selection on levels. Treatment effect approaches address selection on levels but rarely answer the precise question being asked (Heckman & Urzua, 2010). Neither approach identifies causal effects under essential heterogeneity (Heckman et al., 2006).

Structural approaches. Structural approaches, which are also called selection or control function approaches, attempt to model decisions and to predict the outcomes of those decisions based on theory. While Heckman and Vytlacil (2005) focus on economic theory, this description applies equally to a criminological framework in which reoffending outcomes are viewed as a consequence of decisions made by social actors.

A commonly-employed criminological approach to structural modeling in the presence of response heterogeneity is group-based trajectory modeling (GBTM). Rooted in finite mixture modeling, GBTM applications assume that individuals can be better described as following differing developmental pathways or trajectories rather than a single pathway. That is, multiple curves or effects, rather than a single curve or effect, can better describe and explain response heterogeneity (Heckman & Singer, 1984; Nagin, 1999; Bushway, Thornberry, & Krohn, 2003; Haviland & Nagin, 2005; Piquero, 2008; Thornberry et al., 2012). True to Heckman and Urzua's (2010) assertion that structural models are theory-based, GBTM is highly connected to theoretical debates in criminology. For example, GBTM has been used to contrast Moffitt's (1993), taxonomic theory of crime in which offenders follow multiple dynamic developmental pathways, with Gottfredson and Hirschi's (1990) static general theory of crime, which relies on a uniform age-crime curve (Nagin, Farrington, & Moffitt, 1995; Laub, Nagin, & Sampson, 1998).

Manski (1993) outlined the main problems associated with applying structural approaches to the study of social interaction effects: selection, simultaneity, and contextual effects confound peer effect estimates. In short, studies that employ structural models often lack internal validity, meaning the effect estimates they produce fail to accurately characterize the sample under study (Imbens, 2009). In addition to the aforementioned threats to internal validity, structural models have also been attacked for their overreliance on arbitrary and untenable functional form assumptions and for their failure to test fundamental assumptions regarding the decision processes being modeled (Spelman, 2008; Nagin et al., 2009; Angrist & Pischke, 2009: Heckman & Urzua, 2010; Heckman, Humphries, Veramendi, & Urzua, 2014). These critiques apply to criminological GBTM approaches, which assume a curvilinear trajectory (i.e., second-order polynomial) functional form and presuppose, generally without testing for, the existence of groups (e.g., Haviland & Nagin, 2005; Brame, Paternoster, & Piquero, 2012)

As Heckman and Urzua (2010) write, “After 60 years of experience with fitting structural models on a variety of data sources, empirical economists have come to appreciate the practical difficulty in identifying and precisely estimating the full array of structural parameters that answer the large variety of…questions contemplated” (p. 27). Identifying, measuring, and modeling the key variables and processes that generate treatment and outcome decisions is difficult and for some “fundamentally unanswerable” questions can be impossible (Angrist & Pischke, 2009, p.5). Although structural models have value because they apply theory to pose pertinent questions, they often lack internal validity because they are generally not sufficient to convincingly identify causal effects in the presence of selection on levels or unobserved heterogeneity. To address unobserved heterogeneity, strategies that rely on exclusion restrictions must be employed (Heckman, 1976; Spelman, 2008; Fletcher, 2009, 2012; Nagin et al., 2009; Angrist, 2013).

Treatment effect approaches. Treatment effect, or causal, approaches (Imbens, 2009) attempt to identify causal effects of treatment from observational data using exclusion restrictions. Instrumental variables (IV) approaches fall into this category (Imbens & Angrist, 1994). The most common IV approach, two-stage least squares (2SLS), employs variables called exclusion restrictions to characterize a treatment decision and to estimate the effect of that decision on outcomes. The first stage is called a choice model because it characterizes the decision to be treated or to remain untreated. The second stage is called an outcome model because it characterizes how the treatment decision determines outcomes. Exclusion restrictions (or instruments) are variables that predict the treatment decision (i.e., belong in the choice model), but do not predict outcomes except through treatment (i.e., do not belong in the outcome model). Variation in treatment that is attributable to variation in the exclusion restriction (i.e., instrumental variable) is leveraged to identify the effect of the treatment on the outcome.

IV estimation strategies identify gains from treatment by differencing out the levels of the covariates at specific decision points. Differencing out the levels can eliminate biases due to simultaneity and selection on levels or unobserved heterogeneity (Spelman, 2008; Fletcher, 2009, 2012; Nagin et al., 2009). This ensures that the causal effect estimates from IV methods have high internal validity (Imbens, 2009).

Apel, Bushway, Paternoster, Brame, and Sweeten (2008) provided a criminological example of an IV implementation that yields causal effects. Apel et al. (2008) leveraged exogenous variation in state child labor laws to determine that laws that increase the number of hours teenagers can work encourage them to drop out of high school, while also discouraging them from engaging in delinquent behavior. In the choice model, child labor laws predicted hours worked, which in the outcome model, predicted delinquency and high school completion as a function of those additional hours worked.

Although IV estimates may have high internal validity, their external validity can be very limited: the effect estimates they produce, while efficient and unbiased, may not extrapolate beyond the portion of the sample to which they apply. IV techniques do not ordinarily identify average treatment effects (ATE), which apply to the entire sample. Instead, they identify local average treatment effects (LATE), which do not apply to the entire sample.

A LATE equates to an ATE only in the rare circumstance when responses to treatment are homogenous. In the more common case of response heterogeneity, LATEs apply *only to those individuals who switch from the untreated to the treated condition in response to variation in the instrument*. This might happen as a result of a policy. The Apel et al. (2008) study, for example, showed that when teenagers work more, as compared to fewer, hours as a result of the age cutoffs imposed by child labor laws they are more likely to drop out of high school and to engage in less delinquency. The policy that allowed teenagers to work more hours both caused them to drop out of high school and inhibited their delinquency. Importantly, *only the teens who worked more hours as a result of the policy change* were affected.

LATE estimates from IV models are often informally considered policy relevant treatment effects (PRTE) because, as the Apel et al. (2008) study exemplifies, IV techniques are often applied to identify the effect of treatment on those induced to accept it via a policy shift (e.g., Bushway & Apel, 2010, p. 607; Loughran & Mulvey, 2010). However, a PRTE is a very special case of a LATE that answers a very specific question related to that policy: What is the effect of the policy on those to whom it applies?

In addition to lacking external validity, most LATEs are either not policy relevant or not entirely relevant to the research question being posed (Heckman & Vytlacil, 2001; Heckman & Urzua, 2010). For example, the aforementioned Levitt (1996) and Drago and Galbiati (2011) studies answered a policy-relevant research question: What happens to the reoffending behavior of inmates released early due to judicial orders or policies intended to reduce prison crowding? They did not, however, answer the actual question of interest: How does <u>the experience of</u> incarceration affect reoffending?

Heckman and Urzua (2010) also note a different kind of problem with LATE parameters: the populations to which LATEs apply may not be immediately obvious or ever discernible. Akin to difference-in-difference estimators, IV methods remove the endogenous observed covariate information (i.e., the levels) to identify the gains or losses from treatment (i.e., the slopes). As a result, the information contained in the differenced-out covariates cannot later be used to determine which individuals are affected by the LATE. That is, the characteristics of the treated individuals are not recoverable. Therefore, even if a LATE answers the actual research question of interest, to whom the LATE applies remains unclear. Again, this is a consequence of differencing out the levels of the characteristics that contribute to behavior in order to identify changes in behavior.

Finally, the conceptual issues related to answering the exact research question being asked and to determining the individuals to whom detected treatment effects apply do not exhaust the shortcomings of IV strategies. Heckman et al. (2006) show that even though instrumental variables approaches can eliminate unobserved heterogeneity, they break down under essential heterogeneity. When individuals select into treatments based on the potential gains to be had from them, the possibility that they end up at similar decision points through different processes emerges, which implies that their responses to treatments delivered at those decisions points may vary.

An explanation of why IV breaks down in the presence of selection on gains requires some knowledge of the assumptions upon which causal identification of a LATE through IV rests. The two main assumptions are, first, that the instrument be correlated with the treatment variable and, second, that it be correlated with the outcome only through the treatment variable, meaning the instrument cannot be correlated with any unobserved information captured in the error term associated with the outcome.[8] If selection on gains is present, meaning unobserved information about the outcome determines whether treatment is received, then the treatment will be correlated with the outcome in ways unknowable to the researcher and, thereby, captured in the error term. Any instrument that manipulates receipt of that treatment will then also be correlated with the outcome through the unknown information in that error term. This violates the second IV assumption.[9]

The local instrumental variables method. Heckman and his colleagues argue for the unification of the treatment effect and structural approaches because the structural approach focuses on answering relevant theoretical questions, while the treatment effect approach provides a means of answering those questions efficiently and without bias (Heckman & Vytlacil, 2005; Heckman & Urzua, 2010). Bringing those two approaches

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[8] The additional assumption of monotonicity is not necessary for this line of reasoning. In Imbens and Angrist's (1994) work, the monotonicity assumption ensures that individuals at the same value of an instrument respond to treatment in the same way. Monotonicity is not required in Heckman et al.'s (2006) specification.
[9] For a technical exposition, see Heckman et al. (2006, p. 393-7).

together encourages answering relevant theoretical questions in the most rigorous possible manner.

> *"The MTE is a choice-theoretic building block that unites the treatment effect, selection and matching literatures" (Heckman & Vytlacil, 2005, p. 679).*

In a series of papers, Heckman and Vytlacil (1999; 2001; 2005) developed a method they call local instrumental variables (LIV), which estimates marginal treatment effects (MTE) and shows how to convert them into all other treatment effects of interest (e.g., ATE, LATE, PRTE, etc.). They define the MTE parameter in terms of the unobserved utility an individual derives from treatment, then demonstrate that it connects the structural and treatment effect approaches, as asserted above. Heckman et al. (2006) build on that work to show how LIV can be used to estimate causal effects in the presence of essential heterogeneity.

The LIV approach is an extension of the potential outcomes framework, which models binary treatment decisions and the results of those decisions.[10] Like the IV application of the treatment effect approach, LIV is a two-step process in which the first-stage treatment choice model relies on exclusion restrictions for identification. Although it employs instruments, the choice model is a structural model. It must be correctly specified to reflect the decision process being modeled. Additionally, the exclusion restrictions must meet the IV assumptions. If the choice model is correctly specified and the exclusion restrictions are valid, each individual's observed probability of opting into

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[10] Both the potential outcomes framework and the method of local instrumental variables can be extended to multiple treatments (Heckman et al., 2006; Heckman & Urzua, 2010). However, only a binary treatment decision is considered here.

treatment can be predicted after the choice model is estimated. To put this process into an applied framework, after estimating a probit choice model using Stata's *probit* routine, the probability of being treated can be predicted using Stata's *pr* post-estimation routine. The probability of being treated based on the observable information in the choice model is referred to as the propensity score.

In standard IV implementations such as 2SLS, the estimates from the first stage choice model are fed directly into the second stage outcome model. In the LIV method, the propensity score (i.e., probability of being treated) is the main estimator in the second stage outcome model. Outcomes are predicted as a function of the propensity to be treated based on the observable information.

The outcomes estimated as a function of the propensity score are not treatment effects. To calculate the treatment effects, the derivative of the predicted outcome equation is taken with respect to the propensity score. This derivative is called the local instrumental variable (Heckman et al., 2006, p. 397). Marginal treatment effects are the evaluation of this derivative at each value of the propensity score, along its range from zero to one. The intervals along the propensity score can be infinitesimal, depending on the granularity required of the estimates. As is the case with post-estimation of categorical dependent variable models, the MTEs may also be calculated at particular levels of the covariates, depending on whether the covariates were interacted with propensity score and, thus, remain in the derivative (Long, 1997; Basu et al., 2007).

Heckman and Vytlacil (1999, 2005) derived formulas to convert the estimated MTE parameters into all other treatment effect parameters. For example, average treatment effects can be calculated by integrating the MTEs over the range of the propensity score provided the propensity score distribution is supported, as described below and in Chapter 7. Other treatment effect parameters can be estimated using weights derived from the data. Heckman and Vytlacil (2005, pp. 680-681) show how to derive those weights and provide the formulas to calculate local average treatment effects, policy relevant treatment effects, and all other commonly estimated effects, for example, the treatment on the treated (TOT) and intention to treat (ITT) parameters.

The propensity score and its role in LIV. The insight of Heckman and Vytlacil (1999, 2005), which was highlighted by Heckman et al. (2006), is the role played by the propensity score. The propensity score is generated through a structural choice model that characterizes a decision maker's binary decision to opt into or out of treatment. The choice model leverages observable information (i.e., the data) to yield the propensity score, which is a measure of the probability that a decision maker will accept treatment based on the observed utility he expects to derive from that treatment. Like all probabilities, it ranges from zero to one.

Using the propensity score to estimate outcomes is advantageous for at least two reasons.[11] First, the support of the propensity score distribution in the data characterizes the completeness of the information contained in the data so that assessments about the comparability of the treated and untreated individuals can be made. As is the case for all propensity-score based methods, balance on the observed characteristics between the

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[11] A third major advantage of using the propensity score, particularly a score generated by leveraging all the available information via multiple exclusion restrictions, to estimate the outcome equation, is that it always generates positive weights that preserve directionality of the treatment effects, thereby obviating the need to assume monotonicity. Basu et al. (2007) show that this is not always true in the case of a single instrumental variable. Since weights are not calculated for this study, however, this point is not discussed herein. Heckman et al. (2006) provides a technical discussion.

treatment and control groups can be achieved, thereby enabling more valid comparisons between groups that have not been randomly assigned (Rosenbaum & Rubin, 1983, 1984; Apel & Sweeten, 2010b). Second, through the MTE parameters the propensity score, which summarizes the observed information as it pertains to a treatment decision, allows for the characterization of the contribution made by the unobserved information to treatment decisions and outcomes (Heckman & Vytlacil, 2005). The propensity score is inversely related to the collective contribution of the unobserved determinants of the outcomes.

The ability to retrieve information about the effect that unobserved information exerts on outcomes is a unique advantage of the LIV method. In common estimation strategies such as multiple regression and instrumental variables techniques, only the contributions of the observed determinants of outcomes are retrieved. By characterizing marginal treatment effects in terms of the collective contribution made by the unobserved information to outcomes, the LIV method provides otherwise irretrievable information about whether and how much unobserved factors contribute to the outcomes.

Support of the propensity score. Multiple regression and instrumental variables techniques leverage information in the sample under consideration in order to produce average or local average treatment effect estimates. However, some individuals in the sample may not be comparable to any other individuals in the sample. In other words, the sample might include outliers. Including outliers in the analysis is akin to the adage of comparing apples to oranges. Generating estimates of each individual's probability of opting into treatment enables direct comparison of the treated and untreated groups given their propensity scores, so that apples can be compared to apples.

Although propensity scores are assigned to individuals, a characteristic of the study sample is the level of *support of the propensity score* distribution by treatment group. The propensity score distribution is said to have *full support* when, across the distribution of the probabilities of being treated in the sample, there are individuals with the same propensity score, some of whom are treated and some of whom are not. In other words, the treated and control groups are balanced given the observable information that is summarized in the individuals' propensity score. Apples can be compared to apples.[12]

If the propensity score distribution does not have full support, average treatment effect estimates cannot be estimated either because there are individuals in the treatment group who cannot be compared individuals in the control group, because there are individuals in the control group who cannot be compared individuals in the treatment group, or there are treatment probabilities about which the sample contains no information (i.e., no individual in either group has a particular propensity score). These

[12] To visualize full support, imagine an American football field, which is 100 yards long. Across the width of the field are lines marking each yard. The field represents the potential values of the propensity score, demarcated at 0.01 intervals. Each team, call one team "Treated" and one team "Untreated," is lined up on its sideline, getting ready to play. The players stand in order by their propensity scores (i.e., numbers on their jerseys), which reflect their probability of being on the "Treated" team based on their observed characteristics. These are large teams. Each team has 100 players, such that, on each sideline, there is a player standing on every yard line, from goal line to goal line. This is what full support of the propensity score can look like: the Treated and Untreated teams are balanced, given their propensity scores. Full support does not imply, however, that the teams are equal or that their distributions are the same. If there are 1,000 Treated players and 300 Untreated players dispersed randomly on their sidelines, the propensity score still has full support as long as each yard line is populated.

Propensity scores can have partial support. If the Untreated players below the 20-yard line are reassigned propensity scores so that they are now elsewhere on the sideline, the Treated players below the 20-yard line can no longer be compared to any Untreated players. The propensity score only has support above the 20-yard line (i.e., above a 20% probability of being on the Treated team). Propensity score also lack support if there are no observations. If the Treated and Untreated players originally assigned to the 80-yard line and above are reassigned to the 50-yard line, no information about either team is available above the 80-yard line (i.e., above an 80% probability of being on the Treated team.)

concepts are clarified in Chapter 8, which evaluates and discusses the support of the propensity score.

Marginal treatment effects, the propensity score, and information. The LIV method identifies marginal treatment effects over the support of the propensity score distribution (i.e., by comparing the outcomes of treated and untreated individuals with similar propensity scores). In addition to providing a means of assessing the amount and the quality of the information contained in the data, the propensity score enables the characterization of the contribution that unobserved information makes to treatment decisions and to outcomes. That characterization stems from Heckman and Vytlacil's (2005) definition of the marginal treatment effect parameter.

According to Heckman and Vytlacil (2005), the MTE is the return to individuals who are indifferent between being treated and remaining untreated. This definition may seem strange, but it is implicit in an experimental framework. In experiments (i.e., randomized controlled trials), indifference between treatment options is achieved mechanically. Subjects are randomized into treated and untreated conditions, such that neither the preferences of the subjects nor the preferences of the researchers are considered in the determination of the treatment condition. Potential outcomes from treatment are theoretically predicted, but unknown until the results of the experiment are analyzed.

In experimental data, indifference between treatment options is fully determined and expressed by an observed variable: the assigned treatment. In observational data, that indifference is a function of both observed and unobserved factors. If an individual is indifferent between treatment options, the observed factors pushing him toward the treated state must be perfectly balanced by unobserved factors pulling him toward the untreated state and vice versa. In addition to reflecting indifference to treatment options, MTEs can also be interpreted as indifference in the willingness to pay for treatment: the treated and untreated states offer the decision maker equal utility (Heckman & Vytlacil, 1999, 2005).

In the context of the current study, a releasee's decision utility is the value he places on continuing his relationship with his cellmate; it reflects his willingness to stay with that cellmate. If a releasee is indifferent between remaining with or leaving his cellmate, the observed and unobserved components of his decision utility balance, such that at a high propensity to select into a longer duration cellmate relationship based on observables, there is also a high propensity to select out of that relationship based on unobservables.

LIV and essential heterogeneity. When essential heterogeneity is not present, the local instrumental variables method could be used to estimate treatment effects, but it is not necessary. Under simple unobserved heterogeneity or selection on levels, the LATEs returned by instrumental variable techniques equate to ATEs. Likewise, if selection on levels is not present, ordinary least squares regression or matching techniques return ATEs (i.e., there is no response heterogeneity). Furthermore, those ATEs equate to all other treatment effect parameters (Heckman & Vytlacil, 2005; Heckman et al., 2006).

When essential heterogeneity is present, the LIV method, unlike multiple regression or instrumental variables techniques, is able to isolate causal treatment effects. LIV allows for estimation of marginal treatment effects as a function of the propensity to <u>not</u> be treated, which like the propensity score (i.e., propensity <u>to be</u> treated) ranges from zero to one. Defining the MTEs in terms of the propensity not to be treated may seem like an unnecessary obfuscation. It is not. As described earlier, when defined in this way the MTEs provide otherwise unavailable information about the collective contribution of the unobserved information to the outcomes.

Unlike multiple regression techniques that return only a single summary average treatment effect for the sample, and unlike instrumental variables techniques that return a local average treatment effect for only one point or interval on the propensity score continuum, LIV allows for estimation of treatment effects at all points along the continuum of the propensity to not be treated. Those intervals or points at which MTEs are estimated can be theoretically-driven, have policy-relevance, or be exploratory in nature. Furthermore, those MTEs can be converted to all other treatment effects of interest including LATEs and ATEs (Heckman & Vytlacil, 2005, p. 680-681).

With the information in the propensity score, treatment effects can be mapped to the individuals to whom they apply based on what is known about them. That is, treatment effects can be generalized to individuals based on their observed characteristics (Rosenbaum & Rubin, 1983, 1984). While unobservables also play a role in outcomes, understanding how the observed covariates impact individuals' treatment decisions may help researchers to improve upon or avoid harmful outcomes, particularly when specific observable factors dominate treatment decisions and/or outcomes. For example, if only particular racial groups are affected negatively by a prospective shift in public policy, whether to implement that shift can be considered with more clarity (e.g., Reitz, 2009).

Limitations. The LIV method leverages the power of exclusion restrictions in a theoretically driven framework that assumes that individuals make decisions about treatment options that in turn determine their outcomes. It leverages the strengths and overcomes the weakness of both the structural and treatment effect approaches to inference. Still, every method has its limitations, as formulated and particularly when applied to different situations. The main limitation of the LIV method as formulated is that the choice model must be correctly specified. This limitation is discussed in this section. A further limitation of the LIV method as it is applied to detecting social interaction effects is discussed in Chapter 7. That limitation concerns potential stable unit treatment value assumption (SUTVA) violations.

Heckman et al. (2006) make clear that the choice model that identifies the propensity score must be specified correctly to causally identify marginal treatment effects and all other treatment effects that derive from them. "Correct specification" of the choice model from which the propensity score is predicted can, as Basu et al. (2007) observed, seem to imply a revisiting of the problems attributed to structural models: threats to internal validity, particularly unobserved heterogeneity, render the estimates implausible (Imbens, 2009).

Threats to interval validity in the specification of the choice model are less of a concern because omitting exclusion restrictions is not akin to omitting variables. Identification of the choice model rests on the exclusion restrictions. Although different exclusion restrictions generally return different effect estimates because they apply only locally, the correct specification requirement necessitates only that all included instruments are valid. From LATEs, as from MTEs, other treatment parameters can be retrieved (Heckman & Vytlacil, 2005). Omitting exclusion restrictions from the choice mode will reduce the efficiency of the estimates it yields, but their omission will not bias those estimates (Basu et al., 2007).

The utility of global treatment effects. While all other treatment effects can be derived from marginal treatment effects, Heckman and his colleagues argue that their retrieval may be superfluous. Global treatment effects, such as average treatment effects, are often not the treatment effects of most interest. While average treatment effects are the outputs of most multiple regression techniques, response heterogeneity suggests that they have little meaning with respect to characterizing how populations and subpopulations respond to treatment. Similarly, local average treatment effects estimated through instrumental variables may apply to only a very narrow and potentially unidentifiable portion of the population.

Policymakers, in particular, may be concerned with the potential for variability in the direction and magnitude of local average treatment effects that apply only to the specific individuals affected by those policies. They may also be concerned with being able to identify the individuals to whom those marginal effects might apply (Heckman & Vytlacil, 1999, 2005; Heckman et al., 2006; Basu et al., 2007; Heckman & Urzua, 2010). This concern is reflected in the criminological literature that employs group-based trajectory modeling to try to understand response heterogeneity and to target interventions to the particular individuals who need them (Nagin, 1999; Haviland & Nagin, 2005; Piquero, 2008; Brame, et al., 2012).

The work of Heckman and his colleagues may offer a viable alternative to GBTM strategies. In particular, the LIV method offers researchers the opportunity to avoid two problems associated with GBTM methods: the assumption that there are analytic groups, which can be confounded with actual categories of people, and the assumption that trajectories are necessarily curvilinear across behaviors (Brame et al., 2012). With LIV, MTEs can be assessed at minute increments where there is support of the propensity score, which delineates individuals by their observed propensity to be treated. In principle, MTEs can also assume any functional form. Moreover, the LIV method also allows researchers to assess the impact of the things they cannot observe (or simply do not know) in the production of outcomes because those unobservables are related directly to the propensity score. Finally, the LIV method enables researchers to identify the individuals to whom the MTEs apply.

In Summary

This study introduces Heckman et al.'s (2006) concept of essential heterogeneity and Heckman and Vytlacil's (1999, 2005) local instrumental variables technique to criminology. More generally, it is also the first study to apply the concept of essential heterogeneity and the LIV method to the study of social interactions.

Essential heterogeneity arises when observed determinants of a decision affect both the decision itself and the outcomes of that decision. Like ordinary instrumental variables techniques, the LIV method can eliminate selection biases due to unobserved heterogeneity. It can also eliminate selection biases due to essential heterogeneity. This happens not by gathering more observable data, but by recognizing that there are observed predictors of the decision that do not directly predict the outcome. The information in the instrumental variables or exclusion restrictions can be leveraged to identify treatment effects even when information regarding the determinants of the decision and its outcomes is incomplete, as it often is in observational studies. This is particularly true when the structure of the decision process is well-defined (Heckman & Vytlacil, 1999, 2005), as it is in the current study, per Chapters 6 and 7.

The LIV method unifies instrumental variables and structural approaches to estimation to provide precise answers to well-posed research questions. In this study, the well-posed research question is: Do cellmates matter? Specifically, this study estimates the social interaction effects on rearrest and recidivism, defined as rearrest or reincarceration without rearrest, that are generated when releasees interact with criminogenic cellmates. The next chapter will synthesize the theoretical framework developed in Chapter 2 with the analytical method described in this chapter to outline the framework that will be used to estimate those effects.

CHAPTER 4: Prison Peer Effects from Theory to an Analytic Framework

The primary goal of the current study is to answer the question of whether interactions with cellmates influence the reoffending of prison inmates, not how interactions with cellmates influence releasee reoffending. More specifically, the question is whether criminogenic cellmate associations can be causally implicated in the prevalence of the reoffending outcomes of the male members of a first-time release cohort from the Pennsylvania Department of Corrections (PADOC). Both criminological theory and statistical methods necessarily inform the current analysis. To properly inform the analysis, both criminological theory and the analytical method must comport with the underlying process being modeled, inasmuch as possible given the limitations of the data and currently available analytic methods.

The underlying process being modeled in the current study is a decision. At its core, that decision is whether or not two inmates should cell together, as described in Chapter 5. Celling decisions might be made by inmates who request cellmates, by correctional officers who assign inmates to cells, or by counselors who recommend inmates for particular prison programs that require particular cell assignments. Likewise, many factors, including (but not necessarily limited to) inmate characteristics, the composition of the institutional population, prison policies, the physical environment, and correctional officer and administrative preferences might influence what is *fundamentally a binary decision*. Two inmates either end up living together in a cell or they do not. Expected to result from that binary decision-making process are intermediate processes, notably social interactions, and the recidivism outcomes those intermediate processes are predicted to produce.

The local instrumental variables (LIV) method (Heckman & Vytlacil, 1999, 2005) presented in Chapter 3 and the Roy (1951) model upon which it was based can approximate binary decision-making processes. Unlike a basic Roy (1951) model, the LIV method can detect and, if necessary, control for the essential heterogeneity that criminological theory expects to influence that decision. To be clear, the local instrumental variables method eliminates bias due to the influence of the unobserved characteristics of releasees, their cellmates, the prison environment, and any other unmeasured factors that may influence both celling decisions and the recidivism outcomes that result from them.

The operationalization of the LIV model with respect to the nature of the cellmate interactions generated by the cellmate assignment decision is informed by the criminological framework and empirical evidence discussed in Chapter 2. That model, which is developed in this chapter, begins the process of translating the cellmate assignment decision process into a theoretically informed analytical model that can yield causal social interaction effects. It is meant to be illustrative, rather than exhaustive.

The discussion below is intended to take the first step of demonstrating that essential heterogeneity and the local instrumental variables method can be applied to the current criminological inquiry and to many other criminological inquiries. Only specific variables (e.g., criminality, criminal experience, reoffending, and duration of cellmate association metrics) and data limitations relevant to the model are discussed in the current chapter because they highlight how key prison peer effects questions will be answered in subsequent chapters. Other available variables and more general limitations of the data are discussed in Chapter 6. Similarly, an exposition of the local instrumental variables method and its limitations is saved for Chapters 7 and 9, while a discussion of the potential instruments and variables relevant to the choice model described in this chapter will be undertaken in Chapter 8.

Introduction to a Roy Model of Prison Peer Effects under Essential Heterogeneity

Criminological theory predicts the presence of essential heterogeneity in the relationship between social interactions with cellmates and releasee reoffending. To see this, a Roy (1951) model of prison peer effects will be considered and extended to exposit the implicit presence of essential heterogeneity (Heckman et al., 2006) in the current and many, if not most, other criminological inquiries. The extended Roy (1951) model can then be adapted to consider the effect of social interactions with a cellmate on reoffending in the context of the criminological framework outlined in Chapter 2 and the local instrumental variables (LIV) method (Heckman & Vytlacil, 1999, 2005) described in Chapter 3.

Roy (1951) developed a simple model to characterize a labor market participation decision and the outcomes of that decision. The Roy (1951) model remains a fundamental approach to modeling self-selection, as described for a general audience in Autor (2009). Quintessential Roy models consider the effect of education on wages in which wages are related to schooling decisions, particularly the decision to attend college (e.g., Heckman et al., 2006; Heckman & Urzua, 2010; Brave & Walstrum, 2014). In the parlance of the potential outcomes framework, education is the treatment and wages are the outcome. After translation to multiple regression notation, the Roy model schooling decision, therefore, looks like:

$$Wages = A + B(Attended\ college) + E \qquad [1]$$

The preceding model ([1]) is typically a binary schooling decision (e.g., attend college or not) that is used to predict a continuous outcome (e.g., the log of wages), which means it is typically estimated via ordinary least square (OLS) regression. However, the model can be generalized to other treatments and outcomes that reflect different kinds of decision processes. In the current study, the decision process to be modeled is whether to cell two inmates together. Only after that decision is made can prison peer effects between cellmates begin to emerge.

Setting aside the need to operationalize the cellmate assignment decision for a few pages, a simple adaptation of the preceding Roy (1951) model to prison peer effects on reoffending resulting from the decision to cell two inmates together would look like:

$$\textit{Reoffending} = A + B(\textit{Cellmate assignment}) + E \qquad [2]$$

As written, this simple model leaves considerable unobserved heterogeneity (E) in the cellmate assignment decision. In education models like the typical Roy (1951) model, unobserved heterogeneity is often attributed to ability or motivation (e.g., Duckworth, Peterson, Matthews, & Kelly, 2007; Todd & Wolpin, 2003). In crime models like the current one, an analogous unobservable is criminality or criminal propensity, which might influence the propensity of inmates to request cellmate associations or the probability that correctional officers cell particular inmates together (e.g., Gottfredson & Hirschi, 1990; Bushway et al., 2001; Gaes et al., 2004). This concern is indicated on the bed assignment surveys presented in the appendix to Chapter 5, which revealed correctional officer preferences to avoid predation by and victimization of inmates. Adding criminality to the current criminological Roy (1951) model of cellmate assignment yields:

$$\textit{Reoffending} = A + B(\textit{Cellmate assignment}) + C(\textit{Criminality}) + E \qquad [3]$$

As was discussed in Chapter 3, unobserved heterogeneity is not the only type of heterogeneity that criminological theory predicts will enter into the relationship between releasee rearrest and celling decisions. The aforementioned unobserved characteristic, criminality, might influence celling decisions (i.e., which treatment is chosen) just as it influences reoffending outcomes. For example, inmates with heightened criminal propensity who want to learn how to commit different kinds of crimes (or how to commit the same kinds of crimes more efficiently) from their cellmates might seek to be assigned to more criminally experienced cellmates or to spend longer amounts of time with those types of cellmates (Clemmer, 1940, p. 104-5; Shaw, 1966). Unfortunately, an inmate's motives, while perhaps indicated by certain observable characteristics, are in large part unobservable. In this simple model, they are summarized in his criminality. Note that criminality is not the only potential unobservable in this equation. Other unobserved information might include correctional officer preferences, motivations, and behaviors that both influence celling decisions and, potentially, outcomes. Correctional officer behaviors might influence outcomes if, for example, inmates are treated harshly and their tendencies toward defiance are provoked as a result (e.g., Bentham, 1830; Sherman, 1992).

The situation wherein unobserved heterogeneity influences both the independent and dependent variables in the Roy (1951) model is called essential heterogeneity (Heckman et al., 2006). Under essential heterogeneity the current criminological Roy (1951) model would look like the following:

$$Reoffending = A + B(Cellmate\ assignment) + C(Criminality) + D(Cellmate\ assignment*Criminality) + E \quad [4]$$

Criminological theory routinely and implicitly predicts the presence of essential heterogeneity in the production of criminal behavior, the adoption of criminal attitudes, and the augmentation (or abatement) of criminality (Sutherland, 1947; Becker, 1968; Gottfredson & Hirschi, 1990; Bushway et al., 2001; Giordano, Cernkovich, & Rudolph, 2002; Nagin, 2013). For example, rational choice theorists expect both the costs and the benefits of criminal activities to be weighed when the decision to commit crime is considered (Bentham, 1789; Becker, 1968). That decision, particularly in the deterrence and perceptual deterrence literatures, is weighted by a discount rate (Nagin & Pogarsky, 2001; Nagin, 2013), or one's level of self-control, which the general theory of crime argues lies at the root of criminal behavior and all intermediate decisions leading to those behaviors (Gottfredson & Hirschi, 1990; Hirschi, 2004).

As the self-control example illustrates, the implicit presence of essential heterogeneity is not limited to criminological theories favored by economists. Critical to the current study, essential heterogeneity is implicit in the differential association framework presented in Chapter 2. Sutherland (1947) argued that the acquisition of criminal definitions, or criminality, breeds more criminality, which leads to criminal behavior (Matsueda, 1988). The concept of essential heterogeneity is, therefore, intrinsic to the criminological learning theories that motivate the current inquiry into the effect of prison peer effects on reoffending. In the current inquiry, criminality is expected to influence recidivism outcomes (Sutherland, 1947; Clemmer, 1950; Gottfredson & Hirschi, 1990; Bushway et al., 2001). And, as the model in [4] illustrates, criminality is also expected to influence the cellmate interactions that play a role in the production of those outcomes (Bentham, 1830; Clemmer, 1950; Nagin et al., 2009; Mears et al., 2013).

A Limitation of the Data that Impacts the Criminological Roy Model

The main limitation to modeling the cellmate assignment process as it has been described is the structure of the data. As Chapter 6 will indicate, the data that support this study are organized in releasee-cellmate pairs. Each member of the 2006-2007 first-time release cohort is paired with the single cellmate with whom he spent the most time, so each releasee has, by design, already been paired with his cellmate. To maintain the dichotomous nature of the underlying cellmate assignment process being modeled, an additional relationship criterion is needed to differentiate the pairs. Adding that criterion means the choice model, instead of answering the question: this cellmate association or not, will answer the question: this kind of cellmate association or not?

In a criminological framework, differentiating characteristics of cellmate associations might be the characteristics of each pair that reflect their collective criminality or their collective criminal experience (e.g., their relative criminality). However, the discussion of the extant criminological literature in Chapter 2 indicated that, in this primary investigation into prison peer effects, the initial differentiating characteristic of cellmate associations should be their duration.

That duration of cellmate associations should be explored first is necessitated by the uncertainty regarding when prison peer effects can be expected to emerge from cellmate associations and for long they might remain detectable. Expectations about how much time it will take for prison peer effects to emerge and whether they might remain detectable can be made based on previous criminological research. Previous criminological research suggests that prison peer effects will vary with the duration of cellmate associations and their timing within releasees' prison stays, such that social interaction effects amongst cellmates may take some time to become detectable before peaking and then dwindling a bit as the releasees approach their release dates (Clemmer, 1940, Wheeler, 1961, Glaser & Stratton, 1961).

While the prediction that prison peer effects will relate nonlinearly to duration comports with balance theory (McGloin, 2009), it conflicts with differential association theory's prediction of a universally increasing relationship between duration of association and evidence of peer influence (Sutherland, 1947; Warr, 1993). Nonetheless, the parabolic curve that has been attributed to prisonization is the best available prior criminological research upon which to base expectations regarding prison peer effects because prisonization itself is expected to occur through inmate social interactions and cellmates are the inmates expected to exert the most social influence on releasees (Clemmer, 1940, 1950; Wheeler, 1961; Wellford, 1967; Gold & Osgood, 1992).

Incorporating the duration of cellmate association into the current model yields the following adaptation:

$$\begin{aligned}&\textit{Reoffending} = A + B(\textit{Time with cellmate}) + C(\textit{Criminality}) + \\ &D(\textit{Time with cellmate*Criminality}) + E \qquad [5]\end{aligned}$$

The preceding choice model and its resultant outcomes can now be adapted to a two-stage local instrumental variables framework.

Adaptation of the Criminological Roy Model to the Local Instrumental Variables Framework

Most modern criminological studies of peer influence are longitudinal in that they compare the behavior of individuals and their peers in the current time period with individual and peer behavior in one or more prior time periods (e.g., Haynie, 2001; Haynie & Osgood, 2005; Haynie et al., 2005; McGloin & Shermer, 2009). Although prior peer behavior is essentially a decision to engage in antisocial behavior, most studies of peer influence do not attempt to explain the prior decision to engage in antisocial behavior. Instead, the prior peer behavior, which is expected to influence future behavior in the framework of a Roy (1951) model, is taken at face value and used to estimate individual outcomes via ordinary multiple regression methods.

As researchers who have implemented instrumental variables strategies to estimate social interaction effects have demonstrated, the failure to explicitly characterize the prior behavior misses an opportunity for causal inference because unobserved heterogeneity is likely to bias estimates from simple multiple regression analyses of Roy models, whereas two-stage frameworks can control for unobserved heterogeneity (e.g., Heckman, 1976; Imbens & Angrist, 1994; Fletcher, 2009, 2012; Imbens, 2009; Bushway & Apel, 2010). In the context of essential heterogeneity, which is likely to permeate most social interaction effect studies, that missed opportunity becomes even more salient because there are likely to be two sources of bias to combat: bias due to unobserved heterogeneity and bias due to essential heterogeneity (Heckman et al., 2006). Estimates from instrumental variables techniques like two-stage least squares may still be subject to bias due to essential heterogeneity, as was discussed in Chapter 3.

If prison peer effects are to be identified independent of bias due to essential heterogeneity as well as bias due to unobserved heterogeneity, the Roy (1951) model presented in [5] must be adapted to a two-stage framework in which the formation of the cellmate relationship is modeled and the choice of instrument does not impact the external validity of the estimates (Heckman et al., 2006; Basu et al., 2007; Heckman & Urzua, 2010). The two-stage framework employed in the current study is the local instrumental variables framework of Heckman and Vytlacil (1999, 2005).

The first stage. As previously discussed, the current study is limited in that it cannot model the formation of the releasee-cellmate association: that association is taken for granted in the dyadic structure of the data. However, the duration that differentiates releasee-cellmate associations is not taken for granted. The current study can, therefore, model a first-stage that predicts a dichotomous choice regarding the persistence of prison peer relationships. Whether a cellmate association persists long enough to meet a particular threshold of time (e.g., 180 days) or falls short of it is, therefore, the choice of interest in the current criminological Roy (1951) model that becomes the first-stage equation in the LIV framework.

As Clemmer (1940, p. 302) noted, "The speed at which prisonization occurs depends on the personality of the man involved, his crime, age, home neighborhood, intelligence, the situation into which he is placed in prison, and other less obvious influences." Criminological theory, therefore, supports the use of demographic, criminal history, institutional, and prison peer variables, as described in Chapter 6 and Chapter 8, to how long cellmate associations last and the degree to which they engender reoffending (i.e., the choice and outcome models). From the first-stage duration threshold choice model, the probability that a releasee will be celled with a cellmate for at least a particular number of days or not can be predicted.

Time with cellmate =A + B(Instruments) + C(Criminality) +
D(All other variables) + E [6]

As indicated by [6] and described in the preceding chapter, the LIV implementation requires one or more exclusion restrictions or instrumental variables, the choice of which is discussed and validated in Chapter 8.

The second stage. In the local instrumental variables framework of Heckman and Vytlacil (1999, 2005), the predicted probability of being celled with a cellmate for a particular amount of time (i.e., the propensity score) serves as the independent variable in the second-stage outcome model. This second-stage outcome model identifies causal prison peer effects with respect to the releasee's reoffending outcomes.

Reoffending = A + B(Probability of time with cellmate) +
C(All other variables) +
*D(Probability of time with cellmate*All other variables) +*
F(Potential polynomial terms) + E [7]

Through the outcome model, interactions between releasee and cellmate criminality and criminal experience measures can be explored to see if, for example, the relative distance between the criminality and criminal experience of the releasee and his cellmate matter in the production of rearrest or more general reoffending, as predicted by McGloin (2009). The intricacies of the model and the means of exploring the influence of prison peer effects through it will be described in more detail in Chapters 7, 8, and 9.

A note on interpretation. The construction of the current LIV implementation presents a bit of a problem for terminology. Strictly speaking, the marginal and average *treatment effects* identified through the LIV model reference the duration of cellmate association. While discerning whether and when treatment effects due to duration emerge is an important aspect of this study, it is not the primary question of interest. The primary question of interest is whether or not *prison peer effects* emerge through cellmate associations. As described in Chapter 2, prison peer effects are expected to emerge through the interaction of releasee and cellmate criminal experience and criminality characteristics (i.e., social interaction variables), the measures of which are discussed below and in Chapter 6. Although the treatment effects identified by the LIV model will necessarily be discussed first because they are expected to indicate when during prison stays prison peer effects will emerge, the goal of the current study is to identifying prison peer effects, which can be attributed to the social interaction variables described below.

Prison Peer Effect Questions to Be Answered through the Current Study

Through the application of criminological theory to the local instrumental variables method described in the previous chapter, the current chapter, and in Chapter 9, the current study will causally identify prison peer effects. This analysis will take place in two stages, through which several questions will be addressed.

1. Identify duration thresholds wherein prison peer effects might be detected.
    a. Do prison peer effects vary with the duration of cellmate association?
    b. When do cellmate associations begin to produce detectable prison peer effects?
    c. For how long do cellmate associations continue to produce detectable prison peer effects? (That is, do prison peer effects persist?)
    d. Does the relationship between prison peer effects and duration of cellmate association follow a parabolic pattern, as the relationship between

prisonization and time served has been shown to do, and as balance theory seems to imply?

2. When those promising duration thresholds are identified, explore each of them to examine whether social interactions between cellmates produce criminogenic prison peer effects.
    a. Do releasees celled with cellmates with prior incarceration records commit more crimes after their release than releasees who are celled with cellmates who have not been incarcerated previously?
    b. Do releasees celled with cellmates who have more extensive arrest records commit more crimes after their release than releasees who were celled with cellmates who have less extensive arrest records?
    c. Do releasees celled with cellmates who have a higher risk of recidivating commit more crimes after their release than releasees who were celled with cellmates who have a lower risk of recidivating?

The primary questions of interest are those answered by exploring whether the criminal experience and criminality characteristics of the cellmates (i.e., prior incarceration, prior arrest, and recidivism risk) produce discernible prison peer effects on releasees' recidivism outcomes. Before the presence of those effects can be discerned, however, it is necessary to determine where (in time) to look for them.

Key Variables and Their Operationalizations

To answer the questions enumerated in the preceding section, the following operationalizations have been made. Those operationalizations comport with the celling decision process described above and in Chapter 5, adhere to the theoretical framework and the analytical model described in Chapters 2 and 3, and work within the limitations of the data.

Outcome variables. The main outcome variable is a dichotomous indicator of whether a releasee was rearrested for any crime within four years after his release. Prison effects are generally measured at three to five years post-release. A four-year follow-up period is, therefore, necessary to evaluate the hypothesis that interactions with prisons peers can account for criminogenic prison effects. While criminological learning theories do not make strong predictions about whether peer effects can endure for several years, the developmental literature does. Following that literature, prison peer effects are theorized to persist in the post-release period via cascading processes, as described in Chapter 2 (Masten et al., 2005; Dishion et al., 2010).

In addition to the rearrest measure, an additional reoffending measure was derived from the data. The second reoffending measure, termed a *recidivism* measure, includes both rearrest and reincarceration without rearrest. To the best of the ability of the data, the recidivism measure reflects whether a releasee reoffended because the recidivism measure captures reoffending in terms of whether a releasee experienced either criminal justice sanction that is observable in the current data during the four-year follow-up.

Both the rearrest and the recidivism measures necessarily include the agency of the criminal justice system, which must detect the individual behavior that instigates the recording of a rearrest or reincarceration event. This means that the reoffending measures are inseparable conglomerates of offender behavior and the behavior of the criminal justice system. The implications of this duality for the estimation of peer effects are discussed in detail in Chapter 10.

Relative to reconviction or reincarceration, rearrest has traditionally been considered the best indicator of reoffending because it reflects the fewest successive steps taken by the criminal justice system. In the domain of official recidivism measures, rearrest is, therefore, considered to be the clearest indicator that an action prohibited by the state was undertaken or an action proscribed by the state was not (Maltz, 1984; Thornberry & Krohn, 2000; Gaes, et al., 2004; Nagin et al., 2009). However, according to the cross-tabulations in Table 1, 18% of releasees who have been reincarcerated appear not to have been rearrested during the four-year follow-up (n=877). Releasees who were reincarcerated without being rearrested are likeliest to have violated their parole in some way, although some arrests that resulted in reincarceration may have gone unrecorded by the Pennsylvania State Police (i.e., there could be measurement error).

Parole violations may be a result of new criminal offenses or they may be a result of failures to comply with the provisions of parole (Petersilia, 2003; Grattet et al., 2009-2011; Maruschak & Bonczar, 2013). During the most recent years for which the Bureau of Justice Statistics collected data (2012), 82% of parolees were on "active status," meaning they needed to maintain regular contact with their parole officers (Maruschak & Bonczar, 2013). Accordingly, absconding, which means that the parolee's whereabouts are unknown for a period of time, is common with approximately 10% of parolees absconding in any given year. Also common are revocations for failed drug tests, with as many as 16% of parolees in a sample being revoked for failing drug tests (Bonczar, 2008; Maruschak & Bonczar, 2013). These numbers and recent reentry research suggest that the most common technical reasons for revocation (i.e., reincarceration) without rearrest are likely to be drug test failures and absconding (Harding, Morenoff, & Herbert, 2013).

However, recent work by Grattet and his colleagues (2009, 2011) also suggests that parole revocations without rearrest have become increasingly common and may be a result of more serious criminal offenses.

With the current combined PADOC and PSP data, it is impossible to know whether the individuals who were reincarcerated without being rearrested had committed new crimes or technically violated their parole. However, even technical parole violations are reflective of forms of behavior prohibited by the state. As such, they reflect outcomes similar to criminal behavior that can be sanctioned with arrest. Drug use, in particular, remains illegal in Pennsylvania. Releasees who engage in drug use, therefore, commit crimes. Moreover, the argument can be made that absconding is a reasonable measure of reoffending because it is essentially the opposite of trespassing or violating a restraining order: instead of being somewhere prohibited, a parolee who absconds fails to be somewhere proscribed.

The *recidivism* outcome variable, better than the *rearrest* outcome variable, differentiates those who appear to have had no formal contact with the criminal justice system from those who have had some form of contact with the criminal justice system. Conceptually, releasees who have had continued involvement with the criminal justice system are objectively different than releasees who have had no observed interaction with the criminal justice system for the simple reason that the former have engaged in behavior that has resulted in a sanction, while the latter have not. It is, therefore, prudent to create an additional outcome measure to delineate releasees who have evidence of any reoffending (rearrest or reincarceration without arrest) from those who have no evidence of it, in addition to the traditionally accept rearrest measure (e.g., Maltz, 1984; Thornberry & Krohn, 2000; Gaes et al., 2004; Nagin et al., 2009).

*** [Table 1 here] ***

Social interaction variables. Per McGloin's (2009) balance theory and Sutherland's (1947) differential association theory, a releasee's own criminal experience is likely to moderate the prison peer effects generated by the criminal experience of his cellmate. The inmates' criminal experience and criminality varies by prior incarceration (cellmates only), prior arrests, and recidivism risk, as measured by a derivative risk score based on PADOC's Risk Screening Tool. These main social interaction variables are the characteristics through which prison peer effects are expected to operate. They are created to reflect levels of and the relative distance between inmate criminal experience and criminality, which can be interacted in the LIV model.

While these social interaction and outcome variable operationalizations are consistent with the theoretical framework presented in Chapter 2 and the variable definitions, as presented in Chapter 6, they are not entirely consistent with differential association theory, upon which prisonization and balance theories are based, because differential association theory expects definitions or attitudes to be the key means through which criminality is developed (Sutherland, 1947; Matsueda, 1988). For example, although PADOC uses the risk score generated by the RST as a measure of criminality (i.e., risk of recidivism or the proclivity to reoffend), it includes none of the attitudinal or perceptual information included in other actuarial measures of criminality, such as the

LSI-R (Andrews & Bonta, 2000). Similarly, prior incarceration and prior arrest are behavioral measures thought to be indicative of an offender's level of criminality, but they do not measure definitions, rationalization, motives or attitudes. Moreover, because they are official measures, they reflect the behavior of criminal justice system actors in addition to the behavior of the individual inmates under study.

Although it would be advantageous to have attitudinal treatment measures, they simply are not available in the current PADOC sample, as described in Chapter 6.[13] This is a minor limitation for at least two reasons. First, while criminological theory motivates it, the current study does not attempt to test criminological theory. The purpose of this study is to determine whether cellmates exert prison peer effects on releasees. For that purpose, behavioral treatment and outcome measures are likely to outperform attitudinal measures because, in non-incarcerative environments, peers' attitudes toward delinquent behavior have been shown to have less influence on behavior than peers' behaviors do (Warr & Stafford, 1991; Pratt et al. 2010). Second, the association between inmates' behaviors and their attitudes may be less relevant than criminological learning theories presume. In the context of incarceration, Wellford (1973) employed a peer nomination strategy similar to that used in the AddHealth study to examine the relationship between inmates' degrees of prisonization (i.e., adherence to prison social norms) and their social involvement (i.e., clique member or isolate) with other inmates. He found no relationship between the two and concluded that "[t]here is a significant body of research that

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[13] The LSI-R, which PADOC uses, does include attitudinal measures, but the LSI-R data are too incomplete for the current sample to be included in the operationalization. Future work may be able to exploit more complete LSI-R data to execute a better test of differential association theory.

suggests that the relationship between subjective orientation and behavior is not as relevant an association as we have theorized, *except in orientational extremes*" (p. 115, emphasis added).

Duration: detecting and moderating treatment effects. As has been previously discussed, the duration of cellmate association may delineate the emergence, persistence, and subsidence of prison peer effects. Duration may also moderate prison peer effects. After they emerge, whether prison peer effects will continuously build, as predicted by differential association theory (Sutherland, 1947; Warr, 1993), be subject to diminishing marginal returns, or have a parabolic shape, as is implied by balance theory (McGloin, 2009) is unclear. Moreover, as suggested by the empirical prisonization literature, the effect of prison peers may be overwhelmed by anticipatory socialization to prosocial influences (Merton, 1957) as inmates near their release dates (Wheeler, 1961; Glaser & Stratton, 1961; Wellford, 1967).

Prior criminological research provides guidance regarding how long it might take for prison peer effects to emerge, peak, and later subside. Although that guidance rests on evidence that includes only three studies that were undertaken fifty years ago, each of those three studies reported similar findings with respect to the evolution of prisonization (Wheeler, 1961; Garabedian, 1963; Wellford, 1967). Wheeler (1961), Garabedian (1963), and Wellford (1967) found only minimal evidence of prisonization after inmates had been incarcerated for six to nine months. After (on average and approximately) one and a half to two years of incarceration, prisonization appeared strongest, then decreased again as inmates approached their release dates (Wheeler, 1961; Wellford, 1967). The six-month duration of relationship threshold might, therefore, be particularly important, as might the nine-month threshold that Wellford (1967) examined. However, duration is also expected to moderate prison peer effects, not just to delineate where they might be detected. It is, therefore, worthwhile to consider how duration is measured and what that measurement implies with respect to the analytic framework.

As described in Chapter 6, duration with cellmates is measured in days. In interaction with cellmate characteristics, a daily measure of duration implies that each additional day exerts an effect that might be positive, subject to diminishing marginal returns, or negative depending on how prison peer effects evolve over time. Moreover, that moderating effect of duration would likely be very small, so small that it might be undetectable with current statistical methods.

To have a better chance of detecting duration effects it is, therefore, prudent to initially consider whether larger blocks of time spent with cellmates have the potential to impact releasees' rearrest outcomes. By first exploring larger blocks of time, it can be determined whether smaller blocks can or should be delineated later. If effects are not discernible within these larger blocks, which include larger sample sizes, it is unlikely that they will be discernible (or credible) within smaller blocks that include less robust sample sizes. Given that prisonization did not seem to emerge until inmates had been in prison for about a year, and given that PADOC releasees encounter their most stable cellmates around that time, it seems reasonable to begin to examine monthly (30-day) increments to determine whether or not prison peer effects among stable cellmates are an emergent phenomenon and how they evolve (e.g., linearly or nonlinearly) as those associations persist through time. That is, it may be possible to more precisely determine the zenith of prisonization as a result of prison peer interactions.

Criminological Theory Cannot Be Tested Via This Framework

Criminological theory informs the analysis that will be undertaken in the current study. However, as the previous enumeration of the questions to be explored through this study indicates, the current analysis cannot formally test the criminological theories upon which it is primarily based. Matsueda (1988, p. 285) referred to "definitions of law violation" (i.e., criminal attitudes, rationalizations, and motives) as "the crucial variable" in differential association theory. The current study cannot formally test differential association for the simple reason that attitudinal measures that reflect this crucial variable are not available in the administrative data collected from PADOC. Only behavioral measures that must be assumed to reflect those attitudes are available. The current study, therefore, adopts the hypothesis that more criminally experienced cellmates are more likely than less criminally experienced cellmates to excite more criminality in releasees (Warr & Stafford, 1991). While, as Matsueda (1988, p. 285) also pointed out, "some definitions favoring law violation are learned from nondelinquents and some definitions favoring conformity are learned from delinquents," the precedent for adopting this view of the transfer of criminality, as measured by behavior, from more to less experienced criminals abounds, both in the literature prior to Matsueda's (1988) analysis and in the literature that followed it (e.g., Warr & Stafford, 1991; Pratt et al., 2010). The current study also recognizes, however, that the reverse process (i.e., interactions with less criminal cellmates are likely to yield crimino-suppressive effects) is also a possibility (McGloin, 2009).

McGloin's (2009) balance theory has also motivated the current analysis. Again, unfortunately, the data as currently constructed do not support a strict test of her theory. Post-prison outcomes were not available for more than 40% of the cellmates in the sample. Relative outcomes that measure changes in pre and post prison criminal behavior between releasee and cellmate pairs cannot, therefore, be constructed. While a specialized sample of releasees and cellmates who have been released can be constructed to support future work, an assessment of balance theory is beyond the scope of the current study.

In Summary

The Roy (1951) model provides a useful framework in which to consider the impact of decisions on outcomes. The current decision under study is whether to cell two inmates together for a particular period of time. That decision is expected, over time and through the interaction of the two inmates celled together, to generate prison peer effects that persist for several years post-release.

The decision to cell two inmates together is predicted by criminological theory to be subject to essential heterogeneity: unobserved aspects of the cellmate assignment decision-making process may affect both celling decisions and their outcomes. The local instrumental variables framework (Heckman & Vytlacil, 1999. 2005) is an extension of the Roy (1951) model that can be employed to eliminate bias due to essential heterogeneity.

While criminological theory motivates this study in that it predicts that more criminally experienced cellmates with more criminality will exert criminogenic prison peer effects (Sutherland, 1947) on relatively less criminal inmates and vice versa (McGloin, 2009), the current study cannot explicitly test those theories. Prison peer effects, whether they are criminogenic or crimino-suppressive, can be detected, but not explained.

CHAPTER 5: The Pennsylvania Department of Corrections Prison Context

This chapter describes the Pennsylvania Department of Corrections prison system. It includes an overview of the facilities and an outline of a typical day in the life of a PADOC prisoner. The paths taken by the 2006-2007 first time release cohort through the system are described, including an overview of the process correctional officers use to assign inmates to cells and a description of the means through which PADOC inmates may choose their own cellmates.

The structural and facility level data in this chapter come from a variety of sources. State audits of the Pennsylvania Department of Corrections are available from the Commonwealth of Pennsylvania's website. Monthly population reports from January 2000 forward can be downloaded from the Pennsylvania Department of Corrections website, as can documents detailing PADOC policies on topics ranging from inmate abuse to inmate safety. Additionally, Bret Bucklen and Nikki Bell in the Office of Planning, Research, and Statistics at the Pennsylvania Department of Corrections provided special request data on the location, structure, and operational programming of each of the state correctional institutes (SCIs).

With respect to facility operations, particularly cell assignments, no current publicly available literature describes the process that correctional officers use to assign inmates to cells, either in the PADOC system or any other prison system. To begin to understand that process, a survey was distributed through PADOC's Office of Research, Planning, and Statistics to each of the twenty-seven PADOC SCIs in operation in September of 2012. That bed assignment survey, which appears with its results in the appendix associated with this chapter, asked the correctional officers in charge of making bed assignments to list the factors they use to determine who to cell with whom, to describe the cell assignment process, and also to provide copies of any written procedures they use to guide that process. The survey asked about both initial placements (assigning cells to inmates who are arriving at the institution) and within-facility moves. Unit managers at twenty-six of the twenty-seven facilities responded to the survey. While some provided demographic data on their populations, none of them supplied the requested written procedures, which suggests that none exist.

The Pennsylvania Department of Corrections Prison System

Pennsylvania operates the one of the largest state prison systems in the United States. According to the Bureau of Justice Statistics, Pennsylvania housed 36,847 inmates at year's end in 2000. By the end of 2008, when PADOC housed 49,215 prisoners, the PADOC system had grown from the 9th largest in the United States in terms of number of prisoners to the 7th largest (West, 2010).

Currently the PADOC prison system consists of twenty-six facilities that are distributed throughout the state with multiple facilities in some counties. (See Figure 1.) However, between 2000 and 2007, the time period of the current study, the structure of the prison system differed slightly. In January 2000 Pennsylvania operated twenty-five facilities. During the period in which the releasees were housed in the PADOC system, twenty-seven facilities were operational for at least some of the time. Of those twenty-seven facilities, twenty-five housed men, while two housed women. For reasons described below, the current study excludes women, whose prison contextual environments will be examined in future work.

*** [Table 2 here] ***

A majority (ten) of the 2000-2007 PADOC facilities that housed men are designated as medium security facilities or have a dual designation that includes medium, such as minimum-medium (two additional facilities) and medium-maximum (one additional facility). Of the remaining facilities, three are designated as close (i.e., between medium and maximum), six are designated as maximum, and one (the voluntary boot camp at SCI-Quehanna) is minimum security. Table 2 lists the PADOC SCIs and their characteristics.

Some of Pennsylvania's state correctional institutes have specified secondary purposes (their primary purpose being confinement) and have therefore been customized for particular populations. The maximum security institution at SCI-Pine Grove, for example, houses and treats mainly young adult offenders. Similarly, the medium security institutions at SCI-Chester, SCI-Laurel Highlands, and SCI-Mercer respectively have facilities and programs customized to inmates with substance abuse problems, geriatric and mentally ill inmates, and inmates within twenty-four months of their exit dates.

*** [Figure 1 here] ***

The sizes of the populations housed at PADOC facilities vary considerably. Individually, smaller facilities house between 300 and 1000 inmates, whereas larger facilities house several thousand. The capacity of the prison system was expanded between January 2000 and December 2007, as single cells were converted into double cells (e.g., at SCI-Retreat) and facilities were built to accommodate the growing population of prisoners in Pennsylvania. Nevertheless, capacity constraints remained a problem throughout the 2000 to 2007 period during which the first-time releasees were in PADOC custody.

According to the monthly population reports available on the PADOC website, 7,957 beds were added to the PADOC facilities that house men, 3,890 between January 2000 and December 2003 and 4,067 between December 2003 and December 2007. Despite this non-negligible capacity increase of 20% over seven years, most of the facilities continuously operated beyond their capacities. In January 2000, only four facilities were operating at or below capacity. In fact, the system as a whole was operating at 143% of its capacity. Ten facilities operated at 150% of their capacity or more, with some facilities housing almost double the number of inmates they were intended to house (e.g., SCI-Rockview and SCI-Smithfield). From a system-wide perspective, the situation became somewhat less dire by December 2003 when the system operated at 122% percent of capacity. Still seven facilities were operating at greater than 150% capacity and only five facilities were operating at or below their capacity. By December 2007, nearly all facilities continued to operate above capacity. While the system wide overages declined to 111% above capacity, only five facilities operated at or below their capacities. Nevertheless, those overages were 110-120% in 2007, as opposed to 140-200%, which they were in 2000.

General population housing units held 81% of the beds across the PADOC system in 2000 and expanded through 2007 to encompass 90% of all PADOC beds. In addition to general population housing units, some units are dedicated to programming (e.g., therapeutic communities, typically for substance abuse, but also for sex offenders), while some units are dedicated to control or punishment (e.g., restricted housing units, diagnostic and classification units), and still other units are dedicated to providing basic services (e.g., infirmary, mental health, and special needs units). There is some variation across institutions with respect to the volume of inmates the general population and specialized units can hold. Not all institutions have each of the units.

Each of the SCIs in the PADOC system offers some programming meant to address the needs of offenders. While each SCI offers a different mix of specific programs, similar kinds of programs that address similar needs of offenders operate throughout the system. For example, there are programs to treat sex offenders, to address the alcohol and substance abuse problems offenders may have, to curb violence, and to encourage thoughtful reflection and decision making through cognitive behavioral therapy. Additionally, as Figure 1 shows, fifteen of the male SCIs have prison industries that are not commissary distribution centers. There are metal, wood, and print shops, laundry facilities, and industries that produce mattresses, optics, textiles, and soap.

According to PADOC's monthly population reports, less than 0.3% of the inmates in male PADOC facilities are in the infirmary (about 120 male inmates in all facilities) at any given time. A similar number of inmates are housed in beds specifically for the mentally ill. Far more inmates are housed in therapeutic communities (n~1,500), on special needs units (n~1,500), and in administrative (n~750) or disciplinary custody (n~1600) at any given time. The special needs populations are not evenly distributed across the SCIs. At some facilities, services for inmates with special needs dominate. For example, over the study period about half of SCI-Chester's population participated in therapeutic communities. In general, inmates housed in mental health or special needs units make up at most 10% of the facilities' populations (e.g., at SCI-Pittsburgh, SCI-Laurel Highlands, and SCI- Waymart).

Movement of Releasees through the PADOC Facilities

Based on their bed assignments, the 2006-2007 first-time release cohort (n=10,131) entered into the Pennsylvania Department of Corrections system mainly through two facilities, SCI-Camp Hill (32.05%, n=3,247) or SCI-Graterford (44.31%, n=4,489).[14] Upon entry into the PADOC system, first-time admits must be evaluated and classified. The evaluation process unfolds at PADOC's centralized diagnostic and classification center, which is located at the facility at Camp Hill, a city across the Susquehanna River from Pennsylvania's capital city of Harrisburg. Releasees who were initially housed in SCI-Graterford, which is 35 miles from Philadelphia, were typically convicted in Philadelphia and held at SCI-Graterford while awaiting transfer to SCI-Camp Hill, which is generally at capacity. Therefore, initial assignments to facilities at SCI-Graterford and SCI-Camp Hill are part of the initial classification process.

During the diagnostic and classification process, inmates are medically, mentally, and psychologically evaluated. According to PADOC policy, inmates are assigned a custody level within five days. Custody levels, which range in ascending order of

[14] According to PADOC policy, any SCI can receive inmates, who will then be transferred to SCI-Camp Hill. In practice, about a quarter of the releasees entered the PADOC system in this manner. SCI-Pittsburgh, the western intake facility, received 9.70% (n=983) inmates. SCI-Albion received 6.56% (n=665) inmates. SCI-Greene received 7.34% (n=744) inmates. Laurel Highlands and Waymart received two releasees and one releasee, respectively. Although SCI-Pittsburgh is the western intake facility, less than 10% of the releasees entered the PADOC system through that institution. That may be because SCI-Pittsburgh was closed from January 2005 until July 2007, during which time many of the first-time releasees were received.

seriousness from one to five, reflect the potential for an inmate to pose custodial challenges. An inmate's custody level helps to determine the facility to which he will be permanently assigned and the kind of work he is cleared to do (e.g., custody level two inmates can be assigned outside work). Included in the evaluation are assessments about whether inmates are particularly assaultive, suicidal, pose an escape risk, or are in need of separation from all or only particular inmates. Inmates are also introduced to institutional life at SCI-Camp Hill. They receive information about the prison system, prison policies, the services available to them, and their rights and responsibilities (PADOC, 2011).

Whether they began their stays there or not, nearly all of the releasees spent at least some of their prison stays at SCI-Camp Hill; only fifteen of the 10,131 first-time releasees do not have at least one recorded stretch in a double cell at SCI-Camp Hill.[15] Of the 6,884 inmates who did not begin their stay at SCI-Camp Hill, 6,864 were transferred there after being received at another facility (i.e., SCI-Camp Hill was the second facility to which they were assigned). The releasees spent on average 136.4 (SD=169.1) days in the initial classification process, with the modal time spent in that process being 94 days or about three months. For comparison, the average first-time releasee's prison stay lasted just over 2 years, at 27.8 (SD=18.5) months or 847.3 days, with the modal stay being 22 months (663 days). Thus, the process of initial classification, assignment to a permanent facility, and movement to that permanent

[15] Twelve of these fifteen appear to have filtered from SCI-Graterford into other facilities. The other three appear to have entered either directly or via other SCIs into SCI-Laurel Highlands, which is a special needs facility.

facility takes about three months and consumes about one-eighth of a typical releasee's prison stay.

According to PADOC policy, inmates are assigned to facilities based on their custody level, program needs, separations, behavior at SCI-Camp Hill, and bed space. Most releasees stayed in two (27.03%) or three (55.68%) facilities, including the initial classification facility. Twelve percent (n=1,271) of the releasees stayed in four or more facilities including those at Camp Hill and Graterford, with the maximum number of facilities per releasee being one releasee who stayed in eleven different SCIs. Less than five percent of the releasees stayed in more than four SCIs, including SCI-Graterford and SCI-Camp Hill. Each of the 27 facilities operating during the 2000-2007 period housed at least some of the releasees. Beyond initial classification, the SCIs at Houtzdale, Forest, Mahanoy, Somerset, Chester, Coal Township, Albion, Rockview, and Dallas housed the most 2006-2007 first-time PADOC releasees.[16]

Inmates' custody levels should play a large role in determining the level of facility to which they are assigned. Custody level two inmates should dominate in security level two facilities; custody level three inmates should dominate in security level three facilities; and so on such that inmate custody and facility security levels should be

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[16] The releasees who appeared to stay in only diagnostic and classification facilities (n=523) may be missing subsequent bed assignments, may have had short mins, or may have been housed only in dormitories after SCI-Camp Hill. To try to understand which (if any) of these scenarios might dominate, these releasees' stays and their stretches relative to their stays (i.e., bed coverage) was examined. No clear patterns emerged. There were inmates with short stays and long stays, ranging from 1 to about 81 months (mean=20 months). Additionally for these inmates, coverage in terms of the amount of the stay accounted for in stretches in double cells ranged from about 18% to about 100%, with high mean (~90%) coverage. Therefore, some inmates do appear to stay at SCI-Camp Hill for their entire stay. Discerning why is not possible with these data. In addition, there is variability in coverage with respect to double cells. Some inmates may have been assigned to dormitories or the RHU in facilities not SCI-Camp Hill or SCI-Graterford. Finally, there are inmates with short stays who spend them in diagnostics.

highly correlated. However, in practice, there is considerable mixing of inmates with differing custody levels across facilities of differing security levels. For all bed assignments, the correlation between facility security levels and inmate custody levels for releasees is only $\rho=0.22$, indicating a weak correlation. The correlation, $\rho=0.24$, is similarly weak for cellmates. This weak correlation is likely to due to the fact that inmates generally remain in the same facility even as their custody levels change based on their behavior, with custody levels rising with misconduct, and falling with continued good behavior.

A potential explanation for why inmates stay in the permanent facilities to which they are initially assigned is because transfers seem to require considerable administrative overhead. According to PADOC policy, correctional officers wishing to transfer inmates to another facility must submit a transfer petition that justifies the move. Justifications may include problems adjusting to the facility ("negative adjustment") as evidence by bad behavior, medical issues that require services available only at another facility, and other special needs that arise. Additionally, PADOC policy allows incentive-based transfers, whereby inmates can be transferred to more desirable facilities (e.g., closer to home, lower security level) as a reward for good behavior or what is called "positive adjustment." Conversely, "demotional transfers" can result from negative adjustment (Adams, 1992; Toch & Adams, 2002; PADOC, 2011).

*** [Figure 2 here] ***

Once assigned to a permanent facility, inmates typically shuffle between sections, which are akin to units, in that facility. On average, the releasees lived in 7.7 (SD=3.7) different sections. This implies that, across the PADOC system, inmates live in three or four sections within a facility during their stay. According to a unit manager at SCI-Dallas, this shuffling to different sections often happens because units and buildings have different cultures and some inmates prefer one culture to another. For example, SCI-Dallas, which was built in the 1960s, went through an expansion in the 1980s. During that expansion cellblocks J and K were added to the facility. On those cellblocks, the cells are closer together and the walls are thinner, so noise travels more freely throughout them. As a result, those blocks tend toward rowdiness. According to the aforementioned unit manager, younger inmates prefer the newer blocks, whereas older inmates prefer block B, which is smaller and also quieter, or block A, which is smaller still and, due its proximity to the main office, even more staid than block B (personal communication, 2013).

The observation regarding the culture of the blocks at SCI-Dallas is testable with the current data to the extent that misconducts are indicative of rowdiness. During the period from January 1, 2000 through December 31, 2007 there were 15,782 misconducts recorded at SCI-Dallas. Almost 9,000 of those misconducts took place either in cells or on cellblocks. 3,386 of those misconducts took place in cells or the common areas of A, B, J, and K blocks. In absolute terms, the number of misconducts was nearly identical on blocks A and B (n=1,669) to the number of misconducts on blocks J and K (n=1,717). However, blocks A and B hold more beds (n=386) than do blocks J and K (n=317). Nevertheless, assuming equal variance, the rate of misconducts per bed on blocks A and

B over the seven-year period under examination (4.32) was not significantly different (t=-0.263) from the rate of misconducts per bed on blocks J and K during that time (5.47). The observation regarding the age of the inmates on the different blocks at SCI-Dallas is directly testable with the current data. It, too, is unsupported. While the releasees are slightly older on blocks A and B than they are on blocks J and K (33.0 vs. 32.3 years of age, on average), their cellmates are on blocks J and K are older than they are on blocks A and B (38.2 vs. 36.7 years of age on average).[17]

This inability to differentiate between sections based on age or misconducts, suggests that, while the blocks may have different cultures by a measure other than the rate of misconducts, the characteristics of the inmates on those blocks may not be good indicators of those cultures. That is, the observable data does not differentiate culture. It may simply be that some people, regardless of age or race or any other observable characteristic, prefer less rowdy environments. With respect to controlling for the potential for different sections to have different cultures that impact reoffending, contextual fixed effects at the building and section levels may, therefore, be more effective than aggregate individual characteristics.

Whether cellblock cultures influence the shuffling of releasees through sections or not, the releasees also change cells often. On average, the releasees lived in 14.2 (SD=10.1) double cells during their first-time prison stays. Given that the modal releasee

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[17] A unit manager at SCI-Pittsburgh made a similar observation regarding block cultures. It was suggested that the longer-term (browns) inmates in F-block are more invested in the cleanliness of their block and in keeping things quiet there, while the shorter-term (blues) inmates in C-block are rowdier. Further, F-block has some single cells, whereas C-block has only double cells, which suggests that F-block will be quieter because there are fewer inmates.

prison stay lasted 22 months, with the first percentile spending only 5.4 months in prison[18] and the 99th percentile spending 81 months in prison, the releasees changed cells about every two months. This means that, although between-facility residential mobility is rather low, the rate of within-facility residential mobility is quite high, with inmates changing cells about six times per year; and changing blocks about two times per year, on average. According to the bed assignment survey, which can be viewed in the appendix to this chapter, inmates commonly move within facilities for administratively-driven reasons, such as prison programming (e.g., therapeutic communities) and at their own request (i.e., inmate agreements). Inmates' negative or adjustment and other behavior-driven reasons may also compel correctional officers to move inmates.

A Day in the Life of a PADOC Inmate

Below is an outline of the daily schedule at SCI-Dallas as a unit manager described it (personal communication, 2013). A copy of the daily schedule for the F-block at SCI-Pittsburgh appears in the appendix associated with this chapter. As the Dallas and Pittsburgh schedules indicate, inmates are locked in their cells with their cellmates from 9pm, when the last head count for the day begins, until 6:30am, when the first head count of the day "clears" or finishes with all inmates accounted for. In addition, inmates are in their cells with their cellmates during head counts, which take place at three additional times during the day. Head counts take approximately 30 minutes.

[18] Inmates with expected stays of less than 12 months are called "short mins" because they have short minimum sentences.

Therefore, inmates are routinely locked in their cells with their cellmates for 12 hours each day.

*** [Table 3 here] ***

When not confined to their cells, SCI-Dallas and SCI-Pittsburgh inmates are free to move throughout their units (i.e., sections) and the portion of the yard allocated to their unit. They do not typically interact with inmates from other units. Interestingly, yard time is contingent on the timing of the sunset, which means inmates spend more time confined specifically to their cellblocks in the wintertime than they do in the summertime. Between the end of night yard and lock up at 21:00 hours, inmates can move freely in their units.

Without explicit permission, PADOC inmates cannot leave their units or the portion of the prison yard to which they have access. To travel from their section to any other area of the prison, inmates are required to have special credentials. Those credentials differ by facility. At SCI-Dallas, the credentials are akin to hall passes that must be signed and time-stamped by correctional officers on both the sending and receiving ends. (See the appendix associated with this chapter for a sample block pass from SCI-Dallas.) Should an inmate fail to have his pass time-stamped or signed, he could be subject to disciplinary action.[19] At SCI-Pittsburgh, each inmate has an identification card that includes his picture and indicates the areas to which he has access.

By virtue of the fact that they are confined to their units unless they have a specific reason to leave them, inmates spend the bulk of their free time with other inmates who are assigned to the same unit. Inmates routinely leave their sections for meals and exercise, however they do so in the company of the other men in their section and generally in isolation from inmates on other units.[20] Evidence of this unit separation can be seen in the rotation of "blues" and "GP" (general population) inmates housed on F-Block in SCI-Pittsburgh. (See the appendix associated with this chapter.) At SCI-Pittsburgh, inmates who wear blue prison issue clothing are separated from inmates who wear brown prison issue clothing for reasons described below. This separation is maintained through yard, meal, and other times.

Inmates also generally work in the company of their unit-mates. Most SCI-Dallas inmates have jobs on the unit, such as cleaning common areas (personal communication, 2013). Throughout the PADOC system, inmates who work jobs that are not on the unit (e.g., prison industry, kitchen, laundry, or exterior maintenance) are often assigned to the same living quarters as their workmates, due to the proximity of the living quarters to the work environment. This enables correctional officers to monitor inmates at they travel to

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[19] During a prison visit a correctional officer related the story of a recent incident wherein an inmate failed to have his pass signed and was missing from his block for several hours. The inmate was currently serving a sentence in the RHU for that infraction.
[20] During this "shift change," inmates from one section typically exit the cafeteria or gym through one set of doors while the inmates from another section enter through another set of doors. The inmates from different units may, therefore, see each other in passing, but do not have much time to interact (personal observation, 2013).

and from work and also to better maintain facility security, as reported in bed assignment surveys that were administered to correctional officers in each of the PADOC facilities. For example, culinary workers at SCI-Forest are assigned to specific units "to curtail contraband from…spreading throughout the institution." Similarly, at SCI-Dallas "outside workers" who take care of the land surrounding the institution live in O-block. Further, the work-live overlap is generally so substantial that a single correctional officer handles both the cell and work assignments. As one correctional officer reported, "The responsibility of inmate placement initially falls on the Inmate Employment Coordinator when the inmates first arrive at the institution." Thereafter, cell assignments proceed based on medical restrictions, race, and age.

Nevertheless, the policies that assign inmates to cells and to work details are neither perfectly uniform nor likely to be in complete alignment either within or across facilities. Some inmates may live in different units than the majority of their workmates. Therefore, work and school assignments may provide inmates with opportunities to socialize with inmates not on their block. However, the time inmates spend at work or school is still far less than the time inmates spend locked in their cells with their cellmates. Per PADOC policy, a standard workday lasts six hours. While not all inmates have jobs, those inmates who do not have high school diplomas must attend educational programming toward earning their GEDs. Inmates are considered full-time students in the PADOC system if they spend four hours in class per day. Thus, if they work full time, inmates spend half as much time at work as they do locked in their cells with their cellmates; if they go to school they spend at school only one-third of the time they spend locked in their cells with their cellmates.

Whether the time inmates spend with their cellmates is "quality" time in the sense that close personal relationships are fostered during that time and whether the time spent with cellmates is of higher quality than the time spent with work or schoolmates is impossible to know with the current data. The best that can be said of each of those potential relationships is that they, like all relationships, are likely to vary in their quality both absolutely and relative to each other. What can be said definitively is that due to the highly structured nature of the prison environment, cellmates spend absolutely more time alone and in close proximity with each other than they do with any other single inmate.

How Correctional Officers Assign Inmates to Cells

Three major conclusions were drawn from the bed assignment survey, which was answered in narrative form by correctional officers at twenty-six of the twenty-seven PADOC SCIs that were operating in September 2012. First, the process of assigning inmates to cells is neither standardized nor uniform across facilities. However, the correctional officers in each SCI do seem to employ similar strategies when assigning inmates to cells, both at initial placement and for subsequent within-facility moves. Second, although many characteristics of the inmates and their potential cellmates may play a role in the cell assignment process, race and medical restrictions are the factors most critical to that process. Third, in order to really learn how correctional officers assign inmates to cells, they would need to be observed as they performed that task. The first two conclusions were, therefore, investigated during two prison visits during which correctional officers were observed as they made cell assignments.

The state correctional institutes at Dallas and Pittsburgh were chosen for observation because they are both medium security facilities and because one (Dallas) is on the east side of the state one (Pittsburgh) is on the west side of the state. The bed assignment surveys suggested that there might be cultural differences between the eastern and the western facilities, which is why one facility on each side of the state was chosen. As expected, the process of assigning inmates to cells at SCI-Dallas is both similar to and different from that process at SCI-Pittsburgh.

Bed assignments at SCI-Dallas. At SCI Dallas, a single unit manager coordinates the initial placements and within-facility moves that happen daily. For clarity, this person is hitherto called the unit manager coordinator or UMC, even though that is not a formal title. The UMC spends 1-2 hours each day coordinating cell assignments. Anywhere from 50 to 100 initial placements and within-facility moves take place per week.

The cell assignment process at SCI-Dallas proceeds in four general steps. First, the UMC receives a list of inmates being transferred to or moving within the facility. Second, the UMC examines the characteristics of the inmates to be celled using PADOC's online tool, which is called docnet. Third, the UMC references a Vacant Bed Report to match inmates to open beds in the facility. He does this primarily based on the race of both the inmate to be placed and his potential cellmates. Fourth, the UMC confirms the cell assignment with the unit managers, who can recommend against the assignment based on their more intimate knowledge of the inmates already in the unit, particularly the age of the potential cellmate.

Receive a list of inmates to assign to cells. The list of inmates received by the UMC can be a list of inmates being transferred into the facility or a list of inmates being moved from one cell to another within the facility. Inmates being transferred into the facility are said to be on the "van" list, because they arrive on a van. SCI-Dallas receives between ten and fifty van inmates per week. Inmates arriving to SCI-Dallas are always within prison system transfers, typically inmates who have just completed initial classification at SCI-Camp Hill, which supplies the van list. Inmates transfer from SCI-Camp Hill to SCI-Dallas weekly on Wednesdays. In addition to the SCI-Camp Hill transfers, SCI-Dallas, like all PADOC SCIs, may also sporadically receive inmates who are being transferred from other, non-intake facilities. Those between-facility transfers typically happen for two reasons: the inmate being transferred had a disciplinary problem in his previous facility, or an inmate is returning to SCI-Dallas after receiving services only available at another facility (e.g., cancer treatments at SCI-Pittsburgh).

Both of these types of transfers were observed during a prison visit. Although one incoming inmate was unknown to the UMC, he was assumed to have disciplinary problems based on his custody level, which was four. This was confirmed on docnet, where it could be observed that the inmate had multiple recent misconducts. The inmate was placed on a block that had not recently received a potentially problematic inmate with another inmate of similar race and age. Another incoming inmate was known to the UMC, who mentioned the inmate's frequent transfers into and out of mental health treatment. Although not violent and with a low custody level (two), that inmate was considered unstable. He was, therefore, placed in a cell at the top of the range where the correctional officers sit so that they could better "keep an eye on him."

Within-facility transfers nearly always stem from unit managers, who request moves via emails to the UMC. While within-facility transfers can only be requested by the unit managers, they can be initiated by unit managers who want to, for example, separate particular inmates, or by the inmates themselves who have both formal and informal means of making requests, which are described below. The UMC at SCI-Dallas reported that inmates, not correctional officers, instigate most internal moves. Those requests are typically honored, as long as they are perceived to be in good faith (e.g., not for the purpose of predation) because both the inmates and the staff would prefer harmonious inmate relationships to acrimonious inmate relationships.

Examine inmate characteristics. Whether inmates are van arrivals or within-facility movers, the UMC reviews their characteristics in order to assign them to appropriate beds. The van list contains inmates' custody levels and races, but the UMC consults each inmate's PADOC record (i.e., institutional history) via docnet to get a better sense of his needs and characteristics. The most important factors are whether an inmate requires special housing, such as a single cell, ground level (bottom tier) cell, or bottom bunk; whether an inmate's custody level or work detail warrants special housing (e.g., the RHU for custody level 5 or the O-block dormitory for custody level 2 outside workers); whether an inmate is a security threat or formally separated from someone else in the facility; the inmate's race; and his age.

Match inmates to open beds. To make bed assignments, the unit manager at SCI-Dallas is equipped with two lists of available beds, examples of which appear in the appendix to this chapter. The two lists of available beds are generated differently. An office worker who mines PADOC's centralized databases generates the Bed Availability Report (BAR). The Vacant Bed Report (VBR) is generated nightly by correctional officers who report the vacant beds in their units, along with the races of the men occupying the non-vacant beds in those cells. The unit manager who makes the bed assignments prefers to use the latter list to guide his decisions because the most critical information (i.e., current inmates' races and single cell codes) is reported in one place. The single cells codes are particularly important because inmates with single cell (Z) codes may be housed in two-person cells because no single cells are available. This means that the companion bed is not really available, which the VBR, but not the BAR, communicates.

Inmates with no medical, work, or security restrictions are matched strictly on race and, secondarily, age, which is confirmed with the unit managers. With respect to medical, work, and security restrictions, the medical codes need to be adhered to first. Single and bottom bunk inmates are placed in available single cells and bottom bunks, both of which are typically at a premium. Bottom bunks, in particular, are in short supply.

Unless an inmate has a bottom bunk restriction, he is typically placed in a top bunk with another inmate of his own race and, if possible, someone reasonably close to his age. As the prison population has aged, however, more inmates with bottom bunk status are older inmates, so the latter preference is more challenging to meet. This is observed in the data. Although the correctional officers who responded to the bed assignment survey reported similarity in age as a primary criterion for matching cellmates, "similarity" appears to be a broad concept. The average difference in age between releasees and their cellmates is nine years, with the mode being seven years. There is only a very weak correlation between the age of a releasee and the age of the first cellmate to which he is assigned after initial classification (ρ=0.18). By contrast, the races of the releasees and their "first assigned cellmates" are highly correlated (ρ=0.73).

Separations are restrictions on housing particular inmates together. Separations might exist for a number of reasons, including those related to the criminal justice system, those related to personal matters, and those related to institutional security. These reasons often overlap. For example, some common reasons for inmates to be separated include one inmate participating in another inmate's prosecution, an inmate implicated in a crime against another inmate's family member (e.g., rape), and an inmate who has been (or has a known potential to be) victimized by other inmates (e.g., high profile cases, particularly those involving sex offenders). In such cases, these inmates would generally be separated at the facility or section levels so that they cannot physically encounter each other. Separations are typically administered by SCI-Camp Hill, which distributes inmates across the PADOC system. However, the UMC checks for both separations and other security risks, such as escape codes and codes indicating gang or security threat group (STG) membership or severe mental health problems.

The UMC typically tries to spread potentially problematic inmates (e.g., higher mental health codes, higher custody levels, escape risks, and those with STG verification) around the facility. As he makes cell assignments, he proceeds more or less in order by unit so that no single unit is overburdened with potentially problematic inmates. That is, if the UMC had just moved a person with disciplinary problems to section B, he would look to another unit to absorb an incoming inmate with an escape risk code.

Confirm cell the assignment with the unit manager. After the UMC finds an appropriate bed in one of the units, he calls the unit manager to confirm that the placement seems reasonable. During observation, concerns about drastic (e.g., greater than 10 years) age differences seemed to dictate a deviation from the UMC's decision, as was the case housing the transferred custody level four inmate described earlier. However, in a separate conversation, another prison staff member also indicated that some commitment crime types, particularly sexual crimes, might affect placements. In particular, she mentioned that a specific sex offender in the TCU was being housed with an inmate who was soon to be released date because an inmate close to his release date would be less likely to jeopardize his release by victimizing the sex offender.

Bed assignments at SCI-Pittsburgh. As in the facility at Dallas, there is a single unit manager at SCI-Pittsburgh who coordinates bed assignments and who shall also be referred to as the UMC or the unit manager coordinator. The UMC at SCI-Pittsburgh typically uses more information than her counterpart at SCI-Dallas when celling inmates because she faces a more complicated celling environment, with multiple populations, multiple modes of entry into the facility, and more diverse movement throughout it.

With respect to initial placements, SCI-Pittsburgh is similar to SCI-Dallas in that between ten and fifty van inmates are received from SCI-Camp Hill weekly on Wednesday. However, SCI-Pittsburgh also serves as a western intake facility, meaning new inmates arrive daily from county jails, courts, and even from directly from parole offices.

SCI-Pittsburgh receives as many as 100 inmates per week via alternative (i.e., non-van) commitment routes. Many county admits are known about in advance and, therefore, appear on a list similar to the van list. On that list and in the SCI, county admits are separated into parole violators and new commits. Often, alternative admits are not known about in advance, so they are not on any list. For example, a parole officer might call the UMC to let her know that he will be bringing an inmate to the SCI within the hour, as happened during a prison observation. Information about inmates received in this ad-hoc manner is often limited to what correctional officers can observe about the inmate or elicit from him, so SCI-Pittsburgh uses a celling checklist to gather pertinent information about incoming inmates. A copy of the celling checklist appears in the appendix associated with this chapter.

The initial placement celling situation, which includes van inmates, county advance-notice new commits, county advance-notice parole violators, and no-notice county admits, is further complicated by the fact that SCI-Pittsburgh houses inmates who in the facility specifically to receive specialized medical treatments, both in the oncology unit at the SCI and in the medical facilities in the Pittsburgh area, which has a highly developed health care sector associated with the universities in the area. Thus, inmates can be moving to and from SCI-Pittsburgh to outside medical facilities on a near-daily basis.

SCI-Pittsburgh's multi-purpose environment has led to the development of three different populations, each of which has different needs: a general population of long-term inmates, county admits awaiting transfer to SCI-Camp Hill or to the facility from which they were paroled, and an infirmary population, which includes inmates in Pittsburgh for specialized medical treatments and new admits with immediate medical issues, such as the need to detoxify.

The three populations at SCI-Pittsburgh can be identified at a glance by the color of their prison-issue clothing. Permanent, general population inmates wear brown, as do all inmates at SCI-Dallas. Temporary inmates awaiting transfer to other facilities wear blue. Infirmary inmates wear white. The color system helps correctional officers to manage the shifting populations in the facility, particularly the separation between the inmates referred to as browns (permanent inmates) and blues (temporary inmates), which will be described in more detail below. In particular, the temporary inmates in blue should be at SCI-Pittsburgh for a few weeks at most. If an inmate in blue seems to have been in the facility for more time than that, a correctional officer will likely notice, check on his status, and resolve any issues that may have arisen with his transfer.

Summary of the intake process. Immediately upon intake, all inmates are photographed, receive identification cards, and are assigned inmate and control numbers if they do not already have them. Each PADOC inmate has both a control number and an inmate number. Each inmate is assigned a unique control number, such that each inmate should have only one control number, regardless of how many times he is released from and committed to PADOC custody. In contrast, inmates may have multiple inmate numbers because they may have been committed multiple times. Only newly-convicted inmates receive new inmate numbers. Parole violators, for example, are not assigned new inmate numbers; they re-enter the PADOC system under the same inmate number. Therefore, the same person admitted to PADOC multiple times but never on a new conviction will have only one inmate number, whereas the same person admitted to PADOC multiple times after multiple convictions will have multiple inmate numbers.

After they are identified and assigned numbers, inmates are medically cleared (i.e., tested for communicable diseases, particularly tuberculosis) and assigned to cell blocks. If not medically cleared (e.g., if drug or alcohol dependencies are detected) inmates will stay in the intake unit, infirmary, or restricted housing unit, until they can be cleared. Generally speaking, inmates are processed through SCI-Pittsburgh's intake housing unit (IHU) within 72 hours. At SCI-Pittsburgh, although the UMC must sign off on all initial placements and within-facility transfers, the process is decentralized. Unit managers use the aforementioned celling checklist to assist with celling inmates in this more fluid environment. However, the actual process essentially mirrors that at SCI-Dallas, except for an initial step: the separation of blues and browns.

Initial placement in blues or browns. SCI-Pittsburgh filters inmates into housing units based on their receipt status (whether they are a parole violator or a new commit) and special needs. The main determining factor in inmate placement is commit status. Parole violators and new commits are always separated into blues and brown, respectively. For security reasons, color separation is always maintained in the facility. Parole violators are typically viewed as higher security risks because they are temporary admits from "the street" and have, as the UMC said, "street problems," such as drug and alcohol addictions, and higher rates of communicable diseases, like tuberculosis and hepatitis (personal communication, 2013; NRC, 2014). New commits, on the other hand, have typically been incarcerated during trial, so they are already institutionally acculturated. Therefore, upon admit, an immediate division takes place. New commits who will be staying at SCI-Pittsburgh, whether they enter via the van or the county, are put into browns and parole violators who arrive from the county and who will be transferred from SCI-Pittsburgh are put into blues. Additionally, the intake cohorts are typically kept together. That is, unless there is a compelling reason to separate them (e.g., a fight between inmates in the county jail), inmates received on a particular day will be housed with other inmates received on that day.

The celling process mirrors SCI-Dallas, with more information. For most inmates, the unit managers at SCI-Pittsburgh have the following information: commit status, name, and date of birth; anything they can visually observe (e.g., race, stature); and any information the transferring entity (i.e., courts, parole officer) might have provided. For example, the transferring entity typically informs the SCI if a transfer inmate has posed or has unusual potential to pose a security threat. Similarly, a parole officer might indicate that a particular admit is a technical violator, meaning he poses little threat to institutional security.

As was previously mentioned, the celling checklist, which appears in this chapter's appendix, is used to gather more information about admits to SCI-Pittsburgh. It contains ten questions that must be answered regarding inmate age, county of origin, race, stature, mental health, double celling preference, institutional history, criminal history, and "any other relevant information." The any other relevant information category is somewhat nebulous. The UMC and other SCI-Pittsburgh correctional officers repeatedly mentioned that they "get a feel" for each new inmate as he is processed. More concrete information is gathered by directly asking inmates if they have a problem "taking a cellie" or if they have a problem taking a cellie "of a particular race or religion." For instance, according to the UMC, Muslim blacks and Christian whites often prefer to avoid each other (personal communication, 2013).[21]

If, based on the celling checklist information, an inmate is perceived to be a good candidate for double celling (i.e., has no reported conflicts, appears mentally stable, and

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[21] Clustering on religion, particularly for Muslims, is observed throughout the PADOC system.

lacks single-cell status), the UMC attempts to match inmates on as many of the celling checklist metrics as possible, such that inmates with more extensive criminal histories are not with first-timers, older inmates are not with younger inmates, black inmates are not with white inmates, and so on. Inmate preferences, however, are secondary to security. Note, however, that unlike race and age, most checklist items are ambiguous with respect to celling determination. For example, inmates from the same county jail might have a conflict with each other or they might be copacetic with each other.

At the most basic level, intake officers look for any indication that within-facility security might be compromised. At SCI-Pittsburgh, the UMC seemed particularly concerned with victimization. She repeatedly said that the unit managers like to err on the side of caution, especially when it comes to potential for predation. Indications that individuals might be predatory include repeatedly asking for specific types of cellmates or refusing a single cell.

How bed assignments are tracked. Facility-wide, a vacant beds report, which is similar although not identical to the one generated at SCI-Dallas, is generated nightly at SCI-Pittsburgh. Unit managers at SCI-Pittsburgh reference this VBR and their own personal knowledge to cell inmates. Further, due to the antiquated nature of the SCI-Pittsburgh facility, which was built in 1882, analog methods are still employed to track bed availability.

In addition to the computerized system, F block has a physical board in the correctional officers' office on which all bed assignments are tracked. Inmates are housed on the bottom four of five levels in the building that is F block. Each inmate is represented on the board by yellow (for blues) and white (for browns) cards. The cards fit into empty slots that represent beds. Red and white striped cards indicate broken or otherwise unavailable beds. Aside from indicating permanent or temporary status via their color, the each card contains the following information: an inmate's last name, his inmate number, his race, and any medical or housing restrictions he may have. There are "yard" and "river" sides to F-block, which sits on the east bank of the Ohio River and to which the blues and browns are restricted. Blues live on the river side and browns live on the yard side. Blues and browns have separate schedules (i.e., yard time, etc.) so that the separation between them is constantly maintained. The F-block daily schedule, which appears in the appendix associated with this chapter, reflects this separation.

Similarities and differences in the SCI cell assignment processes. While the processes of assigning inmates to cells seem very different in SCI-Pittsburgh and SCI-Dallas, they are actually generally the same. The main difference stems from the fact that SCI-Pittsburgh serves a dual purpose as a general population facility and an intake facility for county-level admits, which means that some inmates have been temporarily assigned to SCI-Pittsburgh, while others have been permanently assigned there. Aside from that difference, the permanent browns at SCI-Pittsburgh are treated just as permanent inmates at SCI-Dallas are. They are given permanent cell assignments based primarily on their special statuses (if they have any), race and age. Similarly, the blues are treated like temporary inmates at an intake facility, such as SCI-Camp Hill. They do not have a permanent housing assignment and are awaiting or participating in the intake process into the PADOC system.

The differing statuses of the browns and blues at SCI-Pittsburgh are reflected in their constant separation. This conceptual and physical separation can be maintained analytically, such that intake and general populations at SCI-Pittsburgh can be treated as separate populations, just like the intake populations at SCI-Camp Hill can be treated separately from the general population of inmates in the bulk of the PADOC system. This also holds true for the inmates committed in Philadelphia who may be held temporarily at SCI-Graterford. Like blues at SCI-Pittsburgh, many inmates only pass through SCI-Graterford on their way to SCI-Camp Hill (or another permanent facility if they are parole violators who can skip initial classification). Other SCI-Graterford inmates are part of the permanent population there.

An additional difference lies in the centralization of the cell assignment process. At SCI-Pittsburgh, the process is more decentralized, with unit managers making celling decisions more or less independently after inmates are assigned to their units. At SCI-Dallas the process is more centralized: a single UMC coordinates cell assignments for the entire facility. Again, these differences are not as striking as they might seem at first glance. At SCI-Pittsburgh, inmates must initially be assigned to a unit or section, as they also must be at SCI-Dallas. Further, even at SCI-Dallas, the unit managers in each section can ultimately dictate cell assignment changes. According to the bed assignment surveys, this is also generally true across other PADOC facilities. For instance, correctional officers reported that:

> "Block officers 'size-up' inmates upon arrival and have discretion to change [a] placement if it appears inappropriate. [This change] is reviewed the following morning,"

and also that:

> "[T]he Unit Manager…directs where the inmate will be placed…As time progresses the Unit Manager utilizes observations and suggestions from the unit security staff [to decide] if changes in bed assignments need [to be] made, [and considers] the inmates own [requests made] via cell agreements."

Therefore, the cell assignment process is ultimately decentralized but proceeds along these summary lines, as outlined by a correctional officer at SCI-Smithfield:

> "Inmates are moved from reception unit to permanent unit as beds become available. Inmates are generally assigned to cells based on age and race. Once assigned to a unit, inmates can sign 90 day cell agreements with inmates they are compatible with. Cell issues that occur on the Unit are resolved by Block Officers and the Unit Team. If needed, cell moves can be done immediately."

The Potential for Inmates to Choose Their Cellmates

In the state prison system in Pennsylvania, inmates can opt to choose their cellmates by making informal and formal requests to cell with a particular cellmate. According to the UMC, inmates are told about the option to request cellmates during intake at SCI-Camp Hill. Informal requests consist mainly of ad-hoc verbal requests to correctional officers. Formal requests are paper documents must be signed by the inmates requesting to be celled together and their unit manager. Examples of the cellmate request documents from SCI-Pittsburgh and SCI-Dallas appear in the appendix associated with this chapter. While the documents for the two SCIs differ, their content is essentially the same; and reflects that the ability for inmates to make cellmate requests is a generalized PADOC policy. The documents make it clear that both inmates and their unit manager must agree to the move, and that the agreement will persist for 90 days during which the inmates cannot request another move and the unit manager agrees not to move them. When the agreement ends, the inmates may continue to be housed together, but without the agreement binding them or the prison management to that arrangement. The agreement may also be renewed.

According to the UMC at SCI-Dallas, about five agreements were active on the UMC's unit at the time of the prison visit, which means ten of the approximately 200 inmates on that unit had entered into agreements in the last 90 days. Unfortunately, records of inmate agreements, such as the agreement forms, are purged almost immediately after the term of the agreement ends so, in the current data, inmates who have lived under agreements for 90 days or more cannot be differentiated from those who have lived together for 90 days or more, but without an agreement.

What drives cellmate requests? From the perspective of the UMC at SCI-Dallas, formal agreements are generally made between two people who have a past history, either outside the PADOC system or within it. With respect to the outside, they may have known each other prior to their incarceration (i.e., are related to each other or hail from the same neighborhood) or they both may know someone on the outside who recommended that they cell together. Within the PADOC system, the two inmates may have met during initial classification at SCI-Camp Hill or they may have met each other on a job assignment. In fact, 2,202 (21.74%) of the releasees celled for the longest period of time with a cellmate they has also celled with at SCI-Camp Hill.

At SCI-Dallas, inmates are the primary drivers of the internal moves. According to the UMC, three main factors motivate these moves: cellmate compatibility, block culture, and cell location. Cellmate compatibility essentially refers to whether or not the inmates get along. Some factors that play a role in whether cellmates are compatible include cleanliness, music and TV preferences, temperament and personality, and the amount of time each inmate prefers to spend in the cell. With respect to the latter criterion, the UMC reported that some inmates look for cellmates who have work assignments that keep them off the block for most of the day. This affords the inmate without such a work assignment more privacy and time alone in the cell. Although the current data do not evince it, the UMC also reported that inmates should be compatible with their blocks, each of which reportedly has a unique culture and character that the unit managers try to maintain.

In addition to an amenable cellmate and a compatible living environment, inmates are also concerned with the locations of cells. Cells at the back of the range (that is, farthest from the single entrance to the block) are the most coveted. If there are two tiers, cells on the top and at the back of the range are the most prized. These preferences, again, reflect a desire for privacy because fewer people walk by upper tier cells and cells at the back of the range and, potentially, a desire for less supervision because the correctional officers work from the top of the range on the bottom tier, where their offices are typically located. These preferences also reflect a desire for comfort: in the winter, opening the door to the block sends a blast of cold air into the cells at the top of the range. In the summer, that blast is of hot air.

Due the fact that some cells are preferred, the correctional officers more tightly control which inmates can live in those cells. As the officers reported on the bed surveys, top tier or back of the range cells are often used to reward inmates' good behavior. For example, one correctional officer wrote:

> "Inmates with an extensive time of positive behavior will be moved to a cell in a more desirable location on the unit, usually upstairs or at the ends of the tiers as an incentive for continued positive behavior."

Institutional approval of cellmate requests. Both formal and informal requests for particular cellmates may be denied, based on both correctional officer preferences and their assessment of the motivation for the move. With respect to personal preferences a unit manager at SCI-Pittsburgh, for example, made it clear that while other unit managers permit "convenience" moves she does not (personal communication, 2013). In contrast, correctional officers at SCI-Dallas reported that inmates housed there are encouraged to enter into agreements. When inmates approach unit managers about agreements at SCI-Dallas, they are typically received amicably because honoring cell requests promotes "institutional harmony," which is in the interest of prison management (personal communication, 2013). This argument was echoed by a correctional officer at SCI-Forest, who wrote:

> "Inmates submit cell agreements with other inmates that are not currently their cell mates. Moves are made to accommodate these cell agreements. The units strive to have inmates submit cell agreements because this stabilizes the population by celling inmates together that have things in common, which reduces the friction between cell mates."

Institutional harmony cannot, however, be prized above the personal safety of inmates. If, for example, correctional officers perceive predation to be the motivation for a particular request, they will block the cellmate request. This was evident in the narratives from the bed assignment survey responses. As one correctional officer reported:

> "Unit managers should also…look for potential housing concerns [such as sexual predation] which may result in victimization. One indicator is an inmate who has had a large number of previous cell partners [even if he has] no past sexual or violent [misconducts]."

This can lead to celling decisions made such that:

> "Inmates who are noted as being physically or mentally weaker may require placement with a similarly situated inmate or require a placement in a cell with closer staff supervision."

This was the case, for example, with the mentally unstable inmate described earlier. A unit manager at SCI-Pittsburgh echoed these concerns by relating a story about an older black inmate who has a preference for young white men, whom he persists in befriending and requesting to cell with, despite his lack of success in getting the unit managers to approve those requests (personal communication, 2013).

The implicit nature of cellmate choice. As the previous discussion illustrates, another way for inmates to "choose" their cellmates or to be assigned to a single cell is misbehavior. An inmate can physically attack or mentally abuse his cellmate. Of course, negative behavior has its costs: if detected, it will likely result in a misconduct conviction that may carry a punishment that includes a stint in the restricted housing unit. In addition, time could be added to his sentence. Therefore, these sorts of incidents are relatively rare. As a unit manager at SCI-Dallas put it:

> "Ninety-five percent of the guys in here just want to do their time with no problems. It's the other 5% you need to worry about."

Of course, an inmate need not be violent to be unpleasant to cell with; he could be favor bad music, be messy, smelly, or just surly. An inmate can, therefore, do things that would not necessarily garner misconducts but that, nevertheless, essentially make life so unpleasant for his cellmates that very few will accept him as a cellmate. This potentiality is evident in the data. While the average releasee had 14 cellmates (SD=9.3) during his prison stay, some releasees (n=221) had more than forty cellmates, with one releasee churning through ninety-eight cellmates during his prison stay. High numbers of cellmates, as the bed assignment survey respondent noted, typically indicate something undesirable about a person, such as a predilection for physical predation or personality problems (i.e., an acerbic nature).

Ultimately, although formal agreements are important, it is important to recognize that inmates who are not shuffling from cell to cell have implicitly settled on a cellmate relationship that they find, if not ideal, at least tolerable enough to allow to persist. Agreements are simply a means of making an implicit relationship explicit. Therefore, although those cellmates who were in formal agreements cannot be distinguished from those cellmates who were not, shorter and single stretches with cellmates can be interpreted as evidence of discontent with a cellmate relationship, whereas longer, multiple stretches with cellmates might be indicative of, at the very least, indifference between the current cellmate and other potential cellmates.

In Summary

With a population of more than 40,000 inmates, the Pennsylvania Department of Corrections manages one of the largest prison systems in the United States. During the time period of the current study (2000-2007), PADOC operated twenty-five male and two female facilities, each of which varied in size and most of which operated at above their capacities.

To assess their educational and therapeutic needs, first-time inmates in the PADOC system are evaluated physically, mentally, and emotionally at the intake facility located at the state correctional institute at Camp Hill. After spending about three months at SCI-Camp Hill, inmates are assigned to a permanent facility where they then serve sentences that last, on average, two years. Most inmates stay in their first post-initial classification facility, although about twenty-five percent stay in three or four or more facilities. While most inmates remain in the same post-initial classification facility throughout their stays, they move frequently within facilities. The average 2006-2007 first-time releasee lived in ten different cells on six different units.

In the two facilities where correctional officer observations were conducted, SCI-Pittsburgh and SCI-Camp Hill, the processes used to cell inmates vary due to differences in the correctional populations, but still share a similar overarching structure. The primary concerns correctional officers try to address when making cellmate pairings include race, age, programming needs, and the inmates' potential for predation or victimization. In both facilities and across the PADOC system, inmates are allowed to select cellmates, subject to correctional officer approval. From the perspective of the correctional officers, inmates look for compatibility in terms of shared interests and schedules in selecting cellmates. Correctional officers vary in their tendencies to tolerate convenience moves.

Inmates spend about twelve hours locked in their cell with their cellmates. While much of that time is during sleeping hours, inmates are also likely to spend considerable non-cell time with their cellmates. Inmates with similar jobs tend to live in the same housing units. Moreover, inmates are confined to their blocks even when not confined to their cells.

CHAPTER 6: Data

The data that support the current study come from the Pennsylvania Department of Corrections (PADOC) and the Pennsylvania State Police (PSP). The PSP provided Record of Arrest and Prosecution (RAP) sheet data, which include complete Pennsylvania arrest histories, whether those arrests occurred prior to, during, or after spells of incarceration. The PSP data supplement data from the PADOC, which contains the bulk of the information that supports this study. With respect to movement into, out of, and through the state prison system, the PADOC data include information on admissions to and releases from prison (including deaths in custody, escapes, and executions), transfers between facilities within the PADOC system, and also transfers to and from court proceedings and external medical care facilities. Importantly, beginning in the fall of 1999, PADOC began to track bed assignments for all inmates in each of the state correctional institutions (SCIs). Movements into and out of specific beds, even for a few hours, are recorded.

In addition to movement data, the PADOC data also include demographic, criminal history, institutional history, and institutional testing data for current and prior PADOC inmates. The demographic data include information about each inmate's age, race, educational attainment, religion, marital status, and military service history. The criminal history data include information about the county from which each inmate was committed, his commitment crime, sentencing date, and maximum sentence length. For cellmates, the number of prior commitments and their timing can be determined. Similarly, the number of times a releasee has been reincarcerated after his initial 2006-2007 release and the timing of those recommitments are available in the data.

Institutional testing data refer to the battery of examinations to which each inmate is subjected during initial classification. Those tests help assign custody levels and risk scores to inmates and to determine what, if any, institutional programming an inmate might be eligible to receive. Data from those examinations include information on an inmate's prior mental health and substance abuse, his current reading and IQ levels, a risk assessment, and an assessment of the inmate's mental fitness when admitted to PADOC custody.

Institutional history data include an inmate's custody and security levels, as well as whether he was involved in any prison misconducts, when those misconducts occurred, and how serious those infractions were. Misconduct offenses range in seriousness from A to E, with E being the least and A being the most serious. Table 4 lists most unique misconduct offenses and their potential seriousness levels, which appear somewhat arbitrary. Offenses classified as most serious, for instance, can include everything from homicide to using abusive language. Inmate custody levels range from a low of one, typically indicating boot camp or community corrections status, to a high of five, which is generally reserved for inmates in the restricted housing unit, whether they are there for administrative or disciplinary reasons. Inmate custody levels are meant to align with institutional security levels, which also range from a minimum of one to a maximum of five. However, in practice inmates at custody levels two, three, and four are typically comingled together and dispersed across facilities, each of which has a restricted housing unit into which inmates can move and from which they typically return to the cell they left.

*** [Table 4 here] ***

Information about whether an inmate served time in restricted housing (i.e., solitary confinement) as a result of misconduct for administrative reasons, is also present in the data. Disciplinary custody typically occurs as a result of a serious (level A or B) infraction by the inmate. Administrative custody can happen for multiple reasons. The most common reason is for an inmate's protection, such as when an inmate has been involved in a capital or high profile (e.g., Jerry Sandusky[22]) case, when a juvenile inmate is moved through an adult facility, and if an inmate is being threatened.

In addition to information about the inmates in PADOC SCIs, information about the SCIs themselves was also gathered. Each PADOC facility is comprised of multiple buildings, which are divided into sections, which correspond to units that are further subdivided into cells. Facilities, buildings, sections, and cells vary markedly in size, so data on the square footage for cells, buildings, and facilities was collected. The tier or floor where each cell is located is also known. The bed assignment data also contain detailed information on the beds themselves, such that the "types" of beds occupied by inmates during their stays are recorded. For example, if a bed is designated for a therapeutic community, that is indicated by the bed type, as are beds designated for the general population. Time spent in a particular bed type is, therefore, an indicator of time spent in certain kinds of programming.

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[22] In 2012, Jerry Sandusky, a one-time assistant football coach under Joe Paterno at The Pennsylvania State University, was convicted of scores of crimes related to the sexual abuse of children over many decades. Those charges included involuntary deviate sexual intercourse and indecent assault.

As the bed type data indicate, PADOC facilities not only have varied physical environments, they also have varied programmatic environments. Those programmatic environments may include therapeutic communities that address drug, alcohol, and/or mental health issues. They may also include programs based in cognitive behavioral therapy that attempt to improve offenders' decision making, and specialized programs for sex offenders, violence prevention, and perpetrators of domestic violence.[23] Currently, PADOC facilities operate an average of ten programs per facility. In addition to therapeutic communities and offender programming, most PADOC SCIs (n=15) have prison industries, some of which offer opportunities for more advanced job training. Those industries include metalworking, woodworking, printmaking, and optics. To account for this programmatic variation, data on whether each SCI has a prison industry and what kind of therapeutic programming is currently offered in each facility were also gathered. (See the SCI Characteristics in Table 2 for information on prison industries and prison programming by facility.)

From the RAP sheet data come information on the prior and (in the case of the releasees) post incarceration arrest events in which the releasees and cellmates have been involved. The RAP sheets reveal that the releasees and their cellmates were collectively arrested more than 500,000 times and charged with more than 1.6M crimes. Arrest events, their timing, and the number of unique charges contained in each were preserved for each of the inmates. While the RAP sheets contain crime type information, that

[23] A discussion of the intricacies and potential efficacy of therapeutic communities and other prison programming with respect to recidivism reduction is beyond the scope of the current study. For more information on prison programming and its recidivism reducing effectiveness, please refer to MacKenzie (2006).

information was not required for the purposes of this study. Studies of specialization or offending versatility that employ more of the information contained in the RAP sheets is planned for future work.

Data Assembly, Cohort Selection, and Data Organization

The correctional data were downloaded from PADOC's Microsoft Access databases on May 21, 2012, converted into Stata format, and cleaned and assembled over a period of two years. Since 2012, requests for RAP sheets from the Pennsylvania State Police have been made periodically through the Office of Planning, Research, and Statistics at PADOC. Like the correctional data, the arrest history data allow for a four-year follow-up.

All inmates released from PADOC custody for the first time between January 1, 2006 and December 31, 2007 were identified based on movements into and out of the prison system. The 2006-2007 release cohort was chosen to allow for a four-year follow-up period, which comports with the prior literature that examines a three to five year follow-up period (Langan & Levin, 2002; Nagin & Snodgrass, 2013; Durose et al., 2014). Following Wheeler (1961) and Nieuwbeerta et al. (2009), the first-time prison inmates in that cohort were isolated to eliminate the potential for prior prison commitments to condition the prison peer effects. The members of the 2006-2007 first-time release cohort are referred to as *releasees*. Their period of incarceration of a releasee is referred to as a prison *stay*.

After the first-time releasees were identified, their bed assignments and the bed assignments of all other inmates housed in the PADOC system during the seven-year study period were used to identify the cellmates with whom they shared double cells during their prison stays. To make the bed assignment data usable, systematic errors in the bed assignments were corrected to ensure that, among other things, multiple inmates did not occupy single beds simultaneously and that single inmates did not occupy multiple beds simultaneously. Other data anomalies, such as negative time in a bed, were similarly corrected prior to matching the releasees to their cellmates.

The first complete year of bed assignment data became available as of January 1, 2000, so only those releasees who were admitted on or after that date were included in the final sample. Female inmates were also excluded from the current analysis for several reasons. Firstly, female inmates are housed in different facilities, so they are not subject to the same institutional environments as are male inmates. Similarly, females are housed in only one tenth as many facilities, so there is far less variation in the housing environments of female inmates, both at the facility and section levels. Finally, both preliminary analysis and preliminary reports from correctional officers suggested that social interactions with other inmates might affect female inmates differently.[24] For instance, the correctional officers in both female facilities expressed the general sentiment that, "[t]he female population can be challenging to manage due to relationships that foster between inmates…problems…surface due to inmates consensually developing relations…that sour." For these reasons, social interactions amongst female inmates will be examined in future work. The final sample for the current study consists of 10,131 male releasees who were admitted on or after January 1,

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[24] Differential susceptibility to peer effects on crime and delinquency by gender is also evident in the extant literature (e.g., Giordano et al., 2002; Kreager, 2007).

2000 and released from PADOC for the first time between January 1, 2006 and December 31, 2007.[25] They were matched to 55,656 cellmates, 9,123 of whom are also releasees. Therefore, only 1,008 releasees are not also in the cellmate cohort, whereas 46,533 cellmates are not in the release cohort.

Each period of contiguous time spent in a double cell with a cellmate is referred to as a *stretch*. On average, 68.8% (SD=26.6, mode=76.0) of a releasee's stay is comprised of double cell assignments. Collectively, the releasees spent more than 175,000 stretches with cellmates during their stays. As that number indicates, many releasees and cellmates spent multiple stretches with each other. A releasee can be paired with the same cellmate multiple times for many reasons, for example, if one inmate leaves the cell temporarily for the infirmary, restricted housing unit, or special programming. Multiple pairings can also happen if a cellmate is released to the community and returned to prison after violating parole.

To organize the data by unique releasee-cellmate pairs, stretches spent with the same cellmate were summed. Stretches that did not last at least one day were excluded. After summation, 144,347 unique release-cellmate pairs remained. The durations of these cellmate associations range in length from 1 to 2,079 days, with a mean of 39.6 days and a standard deviation of 67.5 days. To preserve the temporal ordering of the covariates for causal inference, the PADOC demographic, criminal history, and inmate testing data

[25] As selected based only on release date, the original 2006-2007 first-time release sample included 12,494 inmates. After matching, 53 releasees were excluded from the sample because they did not match to double cellmates, which indicates that they were either always housed in single cells or dormitory cells or a combination thereof. Excluding inmates admitted before January 1, 2000 reduced the sample to 11,290 releasees. Finally, excluding females reduced the sample further to 10,131.

characterize cellmates and releasees based on the most updated information available at the time of the *first* pairing of the cellmate to the releasee.

After the unique releasee-cellmate pairs were isolated, the cellmate with whom each releasee spent the most time in the least number of stretches was identified. This longest duration cellmate association may be entered into explicitly (i.e., via a cell request) or the cellmate may be someone with whom the releasee finds it at least tolerable, and potentially enjoyable, to live: the acquiescence to the association is implicit. On average, releasees take almost about 10.5 months (315 days) to settle into this most stable cellmate association. The longest-duration or most time-intensive cellmate association then lasts an average of 181.6 (SD=144.8) days. For reference, the average time spent with all cellmates, exclusive of longest-duration cellmates, is 28.8 (SD=41.1) days, with the mode being only fourteen days. Almost one-quarter (24%) of the releasees chose celled with another releasee for the longest period of time. Summary statistics appear in Table 6.

Of course, the most stable cellmates are not the only cellmates or inmates with whom the releasees live and interact during their stays. Although the most stable cellmate association may be the most important cellmate with respect to duration and/or intensity of association, other cellmates, such as first and last cellmates, may also be important to a releasee's post-release criminal behavior (Clemmer, 1940). About one-fifth (n=2,200) of the releasees appear to have met their longest-duration cellmate during initial classification at SCI-Camp Hill, another 199 appear to have met him while waiting at Graterford to be transferred to Camp Hill. While some of those most stable cellmates may have been encountered after initial classification, it appears that about one-quarter of the releasees met the cellmate with whom they would eventually spend the most cell time fairly early in their prison stays. With respect to last cellmates, there is a well-known heuristic, the peak-end rule, which predicts that people will remember their most intense and their last experiences in a particular situation (Kahneman, Wakker, & Sarin, 1997; Kahneman, 2011). Interestingly, the most stable cellmate association is the last cellmate association for a quarter of the releasees, whereas the first cellmates association is the most stable association for less than 1% of the releasees, suggesting considerable sorting that could be a result of either inmate or correctional officer preferences or a combination of both (e.g., Crewe, 2007). While cellmate associations beyond the longest-duration cellmate are also potentially interesting, the study of them is saved for future work.

Finally, to help to determine whether social interaction effects operate more strongly between pairs of individuals or groups of individuals (Urberg, 1992; Rees & Pogarsky, 2011), the average characteristics of all the inmates with whom a releasee shared a double cell were calculated. The time each cellmate spent with a releasee was used to weight the collective characteristics of the pool. In analyses where both the longest-duration cellmate and the cellmate pool characteristics are used, the longest-duration cellmate is excluded from the cellmate pool characteristics calculation, which appears in [8] below.

*Pool characteristics = Sum(Cellmate characteristics * Time with cellmate)/Total cellmate time* [8]

In addition to cellmate pool characteristics, the data also allow for assessment of whether social interaction effects can be detected more distally (i.e., between groups of inmates, as opposed to individual inmates). Section, building, and facility indicators can account for fixed aspects of the environment that are common to all inmates who experience them (Manski, 1993; Fletcher, 2009, 2012). Those aspects include things like the varying block cultures that were described by the unit managers at SCI-Dallas and SCI-Pittsburgh and discussed in Chapter 5.

Measures

The correctional data were operationalized in measures that fall into the following categories: demographic variables, institutional history variables, institutional testing variables, institutional context variables, criminal history variables, and cellmate relationship variables. The measures seminal to the current analysis are discussed in the following section. All measures are generated based on the data most recently collected prior to the first pairing of a releasee to the cellmate being referenced (e.g., longest-duration cellmates, first cellmates, or last cellmates). All dichotomous measures are coded zero (0) for no and one (1) for yes. Measures followed by [*] are used to create a derivative of PADOC's Risk Screening Tool, which is described later in this chapter.

Demographic variables. Criminal behavior has been shown to be associated or theorized to be associated with each of these characteristics. The age-crime curve is a ubiquitous criminological construct that depicts the strong mean association of age with decreases in criminal behavior after adolescence (Gottfredson & Hirschi, 1983). Similarly, race, which may be a partial proxy for socioeconomic status, is a consistent predictor of criminal behavior, with black offenders typically demonstrating higher rates of violence and recidivism than white offenders (Blumstein, 1988; Lafree, Baumer, & O'Brien, 2010; Durose et al., 2014). As evidence of stakes in conformity, education, marital status, military service, and (to a lesser extent) affiliation with a particular religion have been shown to have protective effects against criminal behavior (Toby, 1957; Sampson & Laub, 1993, 2003; Warr, 1998; Lochner & Moretti, 2004).

Age: A continuous measure in years, taken upon admit for releasees and from the time of the first pairing with a releasee for cellmates [*]

Black: A dichotomous indicator of whether the inmate is black

Education: A dichotomous indicator of whether the inmate has a high school (grade 12) education [*]

Married: A dichotomous indicator of whether the inmate is married

Islam: A dichotomous indicator of whether the inmate is a Muslim

Military service: A dichotomous indicator of whether an inmate is a veteran

Urban: A dichotomous variable that indicates whether the inmate was committed to PADOC from an urban county. As designated by the 2000 Census, urban Pennsylvania counties are: Allegheny, Beaver, Berks, Bucks, Chester, Cumberland, Dauphin, Delaware, Erie, Lackawanna, Lancaster, Lebanon, Lehigh, Luzerne, Montgomery, Northampton, Philadelphia, Westmoreland, and York

Institutional history variables. Behavior in prison is typically theorized to reflect the potential for continued criminal behavior after release. This is reflected in the concept of "good time" whereby inmates who display good behavior or "positive adjustment" in prison can shave time off their sentences and, conversely in the lengthening of prison stays for inmates who display "negative adjustment" (Adams, 1992; Toch & Adams, 2002). Custody levels indicate the potential for inmates to misbehave in prison. Inmates with lower custody levels are perceived to be at lower risk for negative adjustment to the prison context. Inmates with custody levels of four or five are perceived to be at higher risk for negative adjustment. Custody levels can rise or fall as inmates adjust positively or negatively and as their mental health issues are addressed (e.g., Adams, 1992; Toch & Adams, 2002). While custody levels reflect expectations about future behavior, misconducts, disciplinary custody, administrative custody, and participation in therapeutic communities reflect actual behavior by the inmate that may also influence his post-release behavior. For example, if inmates with substance abuse problems can resolve those issues by participating in therapeutic communities, they may be at lower risk of recidivating (Wexler, 1995; Inciardi, Martin, & Butzln, 2004; Aos, Miller, & Drake, 2007). Although, according to one systematic review of the evidence there is not enough evidence to support a claim that prison therapeutic communities reduce recidivism (Smith, Gates, & Foxcroft, 2006).

> *Custody level*: A dichotomous indicator of whether the inmate's custody level is above three
>
> *Misconducts*: A dichotomous indicator of whether the inmate was found responsible for a level A or B misconduct [*]
>
> *Administrative custody*: A dichotomous indicator of whether the inmate spent time in restricted housing for administrative reasons
>
> *Therapeutic community*: A dichotomous indicator of whether the inmate spent time in a bed designated for a therapeutic community

Institutional testing variables. The information collected from inmates during initial classification may also impact their reincarceration outcomes. At intake, correctional officers record binary indicators of whether inmates report specific behaviors in their personal histories. In particular, inmates report education, mental health, substance abuse, and employment prior to incarceration to the intake officers. Each of these measures is a well-known correlate of criminal behavior, the effectiveness of sanctions, and which inmates are in need of institutional programming in PADOC (Sherman & Smith, 1992; Farrington, 1995; Bushway & Reuter, 2002; Langan & Levin, 2002; Toch & Adams, 2002; MacCoun, Kilmer & Reuter, 2003; MacKenzie, 2006; James & Glaze, 2006; Pollack, Reuter, & Sevigny, 2011).

With respect to the validity of the inmate self-reports, inmates may report specific behavioral problems or medical limitations to receive more lenient treatment, better facility assignments, or less taxing job placements. Additionally, correctional officers may have some incentive to understate the mental health and substance abuse problems of the inmates in order to avoid overburdening prison services. There is no way of verifying the veracity of their self-reports or the accuracy of correctional officer coding of those reports, except to examine how they compare to those of other correctional populations and, as discussed in Chapter 8, to examine how they perform in analyses (i.e., whether they impact housing decisions and recidivism in sensible ways).

Comparisons were made between the responses of the PADOC inmates and the responses of national inmate samples surveyed by the Bureau of Justice Statistics (BJS) and the Office of National Drug Control Policy (ONDCP). The BJS and ONDCP surveys are disconnected from the potential desire to receive services on the part of inmates and the potential need to provide services on the part of the correctional system, respectively, so this source of bias is eliminated in those surveys. Moreover, the BJS and ONDCP samples are temporally consistent with the PADOC sample. Both were taken in 2003, about mid-way through the prison stays of members of the 2006-2007 first-time release cohort. That PADOC inmates report drug and alcohol abuse, mental health problems, and medical disabilities comparable to these other prisoner samples is, therefore, encouraging.

According to a BJS report, 24% of state inmate nationwide reported a recent history of mental health problems, while 49% reported symptoms consistent with mental disorders, per the Diagnostic and Statistical Manual of Mental Disorders, fourth edition (James & Glaze, 2006). These percentages bound those reported by the PADOC releasees and cellmates, about one-third of whom reported mental health problems at initial classification.

It is more difficult to assess whether medical limitations are reported with similar prevalence because it is unclear which conditions are considered medical limitations in the PADOC data. However, the most reasonable interpretation of the data suggests that the PADOC medical limitations data comports with what is generally reported by inmates upon their admission to prison in the states surveyed by BJS. In the most recently available BJS report, Maruschak (2006, 2008) reported that 36% of male state prison inmates report a medical limitation. In contrast, 20% of PADOC inmates report medical limitations, as recorded by correctional officer. This may reflect slight differences in reporting: the BJS statistic includes mental disabilities, whereas the PADOC statistic appears to reflect physical limitations, such as those that require bottom bunk or lower tier cell assignments. Moreover, according to the same BJS report, about 20% of the medical conditions reported are physical, as opposed to mental or learning disabilities, which comports with the PADOC figure (Maruschak, 2006, 2008).

PADOC inmates report slightly more drug abuse than is reported in the most recently available national samples, but report similar alcohol abuse (Mumola, 1999; Mumola & Karberg, 2006; Arrestee Drug Abuse Monitoring II (ADAM II), 2008). In 2004, 69.2% of state prison inmates reported using drugs at least once per week for more than a month and 83.2% reported ever having used drugs (Mumola & Karberg, 2006). In 1997, 51% of state prisoners reported committing their crimes while under the influence of drugs or alcohol. Mumola (1999) concluded that three out of four state prisoners are drug or alcohol dependent. In contrast, 85% of the releasees and cellmates in the PADOC cohorts report having drug problems and 71% report having problems with alcohol. While the PADOC percentages are slightly higher for drugs, they are not unreasonably high. The PADOC percentages comport with the higher end of the range of percentages of arrestees testing positive for drugs via the Arrestee Drug Abuse Monitoring II (ADAM II) program. (Note that ADAM II tests arrestees admitted local jails, not inmates admitted to state prisons. Nevertheless, ADAM II does provide information about drug use specifically in an offending population, such as the PADOC release cohort.) Across the ten ADAM II sites operational in 2003, between 65% and 89% of arrestees tested positive for at least one of ten drugs (ADAM II, 2008, p. 13).

Educational achievement data for national prisoner samples is outdated. In the 1990s, about 50% of prisoners admitted to and released from state prisons reported either graduating from high school or receiving their GED (Beck et al., 1993; Harlow, 2003; Durose & Mumola, 2004). PADOC inmates report more educational attainment than the average state prisoner reports: about 60% report achievement of a twelfth-grade education. Although they report being more highly educated, PADOC inmates report less employment than the national jail inmate samples surveyed by BJS. (Employment information among inmates was only available for jail inmates, not state prisoners.) Of course, jail inmates are not state prison inmates, so this could account for some of the difference, as might whether PADOC inmates report only full-time, as opposed to full-time and part-time employment, which is unknown. About one-quarter of PADOC inmates report some form of employment immediately prior to incarceration, whereas 60% of jail inmates reported some form of employment (full-time, part-time, or occasional) before being arrested (James, 2004).

> *Mental health problems*: A dichotomous indicator of whether the inmate reported past mental health (psychological or suicidal) problems at initial classification
>
> *Substance abuse problems:* A dichotomous indicator of whether the inmate reported past alcohol or substance abuse problems at initial classification [*]
>
> *Medical limitations:* A dichotomous indicator of whether the inmate reported having a medical limitation at initial classification
>
> *Prior employment:* A dichotomous indicator of whether the inmate reported having a job prior to incarceration at initial classification
>
> *IQ:* A continuous measure of an inmate's IQ

Institutional context variables. Although much has been made of the potential for overcrowding to incite reoffending, little evidence that overcrowding increases recidivism has been generated (Farrington, 1980; Gaes, 1985). Additionally, violence in prison seems to have declined, even as prisons have become more crowded in recent decades (Diulio, 1987; Useem & Kimball, 1991; Crewe, 2007; NRC, 2014). Privacy, however, remains a concern in confined spaces (Adams, 1992; Crewe, 2007). Privacy may also help to determine how much time cellmates spend together. For example, cells in better location (e.g., higher level tiers) or that afford more space (e.g., square footage) are generally perceived to be more attractive, by both inmates and correctional officers. Inmates assigned to those cells might be wont to leave them, even given a less than desirable cellmate association. Therefore, information regarding these aspects of the cells is included in the data.

Cell size: A continuous measure of the square footage in a cell

Cell tier: A dichotomous measure of whether a cell is on a lower (0) or an upper (1) tier

Criminal history variables. Prior criminal behavior has been shown to be among the best predictors of future criminal behavior (Gendreau, Little, & Goggin, 1996; Kurlychek, Brame, & Bushway, 2006; Blumstein & Nakamura, 2009). For this reason, multiple variables that characterize an inmate's prior offending are included as predictors of both celling assignments and recidivism outcomes. Each of these variables are included in or derived from official records.[26] For example, the extensiveness of an inmate's prior record and the seriousness of his current offense are reflected in his maximum sentence (Pennsylvania Commission on Sentencing (PCS), 2012).

Maximum sentence: A continuous measure of the inmate's maximum possible sentence in months

Stay length: Length of the inmate's current stay of incarceration in months (i.e., time served

Prior arrests: A continuous measure of the number of times the inmate was arrested prior to the current stay [*]

Three charges: A dichotomous indicator of whether the inmate's most recent arrest included three or more charges. (This is an LSI-R risk indicator.)

Under 18 at first arrest: A dichotomous indicator of whether the inmate was aged 18 or younger at the time of his first arrest on record with PADOC [*]

Ever violated community supervision: A dichotomous indicator of whether the inmate has a parole violation on record [*]

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[26] Sixteen releasees and Ninety-six cellmates are missing RAP sheets. For these releasees and cellmates, crime types associated with their incarceration offense were used to generate the prior offending dummy variables. The dummy variables are zero in the absence of information.

Cellmate relationship variables. The seventh proposition in Sutherland's differential association theory states that differential associations may vary in their frequency, duration, priority, and intensity. These concepts are not independent, as has been noted by empirical researchers in the differential association tradition since Short's initial tests of the theory (Short, 1956, 1958, 1960; Matsueda 1988; Warr, 1993, 2002).

Burgess and Akers (1966) argued, that "[t]he concept of *intensity* could be operationalized to designate the number of the individual's positive and negative reinforcers" (p. 164, emphasis in original), a conceptualization that Haynie's (2002) operationalization of an "excess of definitions favorable to delinquency" (Sutherland & Cressey, 1955, p. 78), reflects. She operationalized Sutherland's (1947) concept as the proportion of delinquent peers in a friendship network. A similar operationalization, [8], was used in the current study to characterize the cellmate pool: cellmate characteristics were weighted by the proportion of a releasee's stay spent with the cellmate (i.e., the number of days the cellmate spent with the releasee relative to the total amount of time the releasee spent in prison).

In this study, the main modality that moderates the analysis is the duration of the association of a releasee with his cellmate. Whether that duration is contiguous or spread over multiple stretches may be relevant, as it captures Sutherland's (1947) notion of frequency. For example, the return of releasees to their prior cells or cellmates after an administrative separation reveals a clear preference, whether attributable to releasees or correctional officers, to maintain that releasee-cellmate association. Moving away from and back to a particular cellmate, therefore, captures the frequency of association that may be embedded in the duration of association metric.

How much time a releasee spends in prison before encountering a particular cellmate might also matter because it reflects Sutherland's (1947) prediction that associations made earlier in life might be more relevant. Clemmer (1940, p. 102) echoed this importance in his adaptation of differential association to the prison context. However, empirical research in prisons contradicted this prediction. Wheeler (1961) found that time to release seemed to matter more because inmates may begin to disassociate with their fellow inmates as they anticipate their impending release (Glaser & Stratton, 1961; Garabedian, 1963, Wellford, 1967). Therefore, a measure of time to release at pairing was included.[27]

Stretches. A continuous measure of the number of times a releasee was paired with a cellmate

Time to release: A continuous measure of the number of days a releasee had until his release at the time of pairing with his cellmate

Recidivism risk. In the current study, recidivism risk scores serve as measures of observed criminality. They are conglomerate measures of the constituent factors thought to determine an inmate's propensity to reoffend (Andrews & Bonta, 2000; Bushway et al., 2001). As discussed in Chapter 2, PADOC currently uses both the Level of Services Inventory-Revised (LSI-R) and its own Risk Screening Tool (RST) to assess each inmate's recidivism risk. In the current data, however, both risk score variables either do not exist (because the RST was not yet implemented) or are too incomplete (due to inconsistent LSI-R testing) to use. Although the LSI-R includes too many lifestyle

[27] Note that, due to collinearity, both time to cellmate and time to release variable cannot be included if time served is also to be included. Time served is a key and quintessential variable in the measurement of both prison effects and prison peer effects (Bayer et al., 2009; Loughran et al., 2009; Nagin et al., 2009; Snodgrass et al., 2011).

variables to be credibly adapted using the current data, the RST can, with some modifications, be reconstructed using the current data. Shortcomings of employing the recidivism risk score as a measure of criminality were discussed in Chapter 4 and will be explored further in Chapter 10. The primary shortcoming is the absence of attitudinal indicators in the score, which does not capture definitions (Sutherland, 1947) well.

*** [Table 5 here] ***

Reconstructing the RST. The PADOC's Risk Screening Tool is an in-house risk classification assessment tool developed by Bret Bucklen, the Director of Planning, Research, and Statistics at PADOC. The RST has been tested in Pennsylvania and found to be nearly as reliable as the LSI-R (PADOC, 2012). The RST consists of seven indicators and has a range from zero to nine. A copy of the original RST instrument appears in the appendix associated with Chapter 2. The adaptation of the available data to reconstruct the RST is presented in Table 5 and discussed for each indicator in the RST.

Reconstructed RST: A continuous measure of the recidivism risk of an inmate that is based on an adaptation of PADOC's Risk Screening Tool with the available data

Age 18 or under at first arrest: A dichotomous indicator of whether the inmate was under 18 at the time of his first arrest (1 point or 0 points). The original indicator for the RST was under 16 at time of first arrests. Although the PSP RAP sheet data do include some juvenile arrests, because they are adult arrest histories they do not reliably include juvenile arrests, so the threshold was raised. To the extent that inmates who were arrested at age 18, but not arrested at age 16, this measure will inflate the overall RST metric

RST age: A categorical indicator of whether an inmate is 24 or younger (2 points); between 25 and 43 years old (1 point); or older than 43 (0 points)

RST arrests: A categorical indicator of the number of prior arrests, which indicates whether an inmate has two or fewer arrests (0 points) between three and five arrests (1 point) or six or more arrests (2 points) prior to incarceration. The original RST indicator was prior convictions. The PADOC data do not include prior convictions, but they do include adult arrest histories. According to Durose (2007), individuals are arrested, on average, three times for every conviction, so this indicator was operationalized to reflect that average behavior. To the extent that convictions were more or less frequent with respect to arrest, this measure might under- or over-estimate risk in the RST metric

Misconducts: Indicates whether an inmate was charged with an A or B level misconduct (1 point)

Community supervision violations: While the current data to not include data from probation and parole, they do contain information on parole violations that resulted in recommitment to prison. To the extent that inmates may have violated community supervision either prior to an initial PADOC commitment or violated community supervision without incurring a recommitment, this measure will understate risk in the RST metric (1 point)

Education less than grade 12: Indicates whether an inmate has less than a high school education (1 point)

Alcohol or drug problem: Indicates whether an inmate reported having an alcohol or drug problem. While the RST scoring instructions specifically instruct the correctional officer scoring the tool to make their own assessment about whether an inmate has an alcohol or drug problem, this is likely not the case in the general initial classification battery. However, this metric is the best indicator available in the data to assess whether an inmate might have an alcohol or drug problem. To the extent that inmates self-report substance abuse problems when they do not have them, this measure will inflate the RST metric (1 point)

Variables Pivotal to the Current Analysis

Outcome variables. As discussed in Chapters 2 and 4, outcomes based on arrest records are the main outcomes to be explored in the current study. Reincarceration outcomes can be explored in future work, although reincarceration without arrest is included in the second outcome measure, described below. The potential shortcomings of these outcome variables were discussed in Chapter 4 and will be explored further in Chapter 10. Those potential shortcomings include the absence of attitudinal measures, the inability to separate individual behavior from the agency of the criminal justice system, and the binary operationalization of the outcome.

Rearrest: A dichotomous indicator of whether a releasee was rearrested for any offense within four years after his release

Any recidivism: A dichotomous indicator of whether a releasee was rearrested within four years after his release or reincarcerated without being rearrested within four years after his release (877 releasees were reincarcerated without being rearrested)

Differentiating/moderating variable. As discussed in Chapters 2 and 4, the duration of cellmate association is expected to delineate where prison peer effects can be detected. It is also expected to moderate them.

Duration of association: A continuous measure of the number of days a releasee and a cellmate celled together

Social interaction variables. As discussed in Chapters 2 and 4, the main variables of interest in this study are social interaction variables that reflect criminality and criminal experience characteristics of the releasee-cellmate association. In particular, differential exposure to potentially more criminogenic cellmates is hypothesized to foment future criminal behavior. The first three variables listed below reflect level characteristics of the inmates' criminal experience and criminality. The latter two reflect the distance between the releasee and his paired cellmate in terms of criminality (i.e., recidivism risk) and prior arrests. The first-time releasees by definition have no prior incarcerations. As was mentioned above, the shortcomings of these variables with respect to construct validity and the implications of those shortcomings for the analysis are discussed in Chapters 4 and 10.

Cellmate prior incarceration: A dichotomous indicator of whether the cellmate had been incarcerated prior to his current prison stay

Inmate prior arrests: A continuous measure of how many times a releasee or cellmate had been arrested prior to his current prison stay

Inmate RST: A continuous measure of a releasee or cellmate's recidivism risk

Relative number of prior arrests: A continuous measure of the difference between the cellmate's number of prior arrests and the releasee's number of prior arrests. Positive numbers indicate that the cellmate is more criminally experienced than the releasee. This measure follows the operationalization of McGloin (2009).

Relative RST: A continuous measure of the difference between the cellmate's RST score and the releasee's RST score. Positive numbers indicate that the cellmate is at higher risk of recidivism than the releasee. This measure follows the operationalization of McGloin (2009)

Potential instrumental variables. As discussed in Chapters 3 and 4, exclusion restrictions are required to identify the choice model in the local instrumental variables framework. These choices will be more thoroughly discussed in Chapter 8.

Cellmate time to releasee: A continuous measure of how long a cellmate had been incarcerated before being paired with a releasee

Cell size: A continuous measure of the square footage of the cell into which a releasee was initially placed

Cell tier: A dichotomous measure of whether the cell into which a releasee is initially placed is on a lower (0) or an upper (1) tier

The Characteristics of the Cohorts

The release and cellmate cohorts combined contain 56,664 unique individuals. For simplicity, the characteristics of the releasees are reported based on their commitment dates, while those of their cellmates are reported with respect to the time of their first pairing with any releasee. (See Table 6.)

On average, the releasees are 42% black, 14% married, and 30 years old, whereas their most stable or longest-duration cellmates are 45% black, 15% married, and 32 years old, on average. The commit years in both cohorts range from 1968 to 2007. In terms of post-release offending amongst releasees, 58.45% (n=5,922) of the releasees have at least one post incarceration arrest on their RAP sheets during the four-year follow-up, while 67.27% (n=6,815) were either rearrested or reincarcerated without being rearrested at least once before the end of the four-year follow-up.

The releasees and the cellmates differ substantially with respect to their criminal histories. By definition, none of the releasees had been incarcerated prior to the current prison stay, whereas 29.66% (n=3,005) of the longest-duration cellmates had been previously incarcerated at least once. Fifteen percent (n=1,503) of the cellmates are known parole violators. The stable cellmates also have more prior arrests (6.7), on average, than do the releasees (5.5). The average RST scores associated with the cellmate cohort (4.8) are also slightly higher than they are for the releasee cohort (4.5). Collectively, the greater criminal experience and heightened criminality of the longest-duration cellmates relative to their releasees suggests that, on average, those cellmates should exert criminogenic prison peer effects on the releasees.

*** [Table 6 here] ***

Limitations of the Data

As previously discussed, there may be some measurement problems associated with the self-report measures stemming from the initial classification battery of questions. Inmates may have incentives to under or over report specific conditions and experiences. Correctional officers may have incentives to record specific conditions and experiences incorrectly. However, the data overall are very complete, suggesting fastidiousness on the part of the correctional officers who record inmates' information. In fields where scores, grades, or categorical information such as race, marital status, and religion are recorded, there is essentially no missing data and the data that are recorded appear to be recorded with very few errors in that the means and standard deviations are reasonable and there are few outliers. For example, the IQ measures have a mean (91) slightly below normal (100), as expected. Moreover, only ten inmates have IQs below 50, including four zeroes; and only 19 inmates have IQs above 140. The completeness of the recording and the consistency of the known metrics with other samples suggest that the other metrics are recorded with similar accuracy. Furthermore, the statistics derived from the PADOC data related to mental health, substance abuse, and other mental and physical limitations comport with those taken from national samples.

As this is a study of celling decisions and the social interactions that stem from them, there may be some concern regarding the paucity of information available in the current data regarding correctional officer preferences and the correctional environment more generally. For example, information regarding cell locations, beyond their tier, is not available. Nor are, for example, surveys of correctional officers that might indicate varying preferences regarding initial cellmate placements and tolerances for convenience moves.

It is important to recognize, however, that these data limitations are minimized in the local instrument variables (LIV) framework. As described in Chapters 3 and 4, the LIV framework adapts to the presence of both unobserved and essential heterogeneity. Therefore, these data limitations are less important in the context of the current analysis, which is causal despite them. Moreover, while the unobserved heterogeneity is characterized in its entirety (i.e., with respect to all of its component elements) within the context of the method, the method represents a step forward in that it is able to characterize the contribution of the heterogeneity to variation in the estimates.

Finally, as has been mentioned in previous chapters, the administrative data from PADOC and PSP do not include attitudinal measures. While the LSI-R does include some attitudinal measures, the LSI-R scores are too incomplete in the current sample to be useful. Moreover, the attitudinal measures cannot be separated from the behavioral measures in the data currently available: only the total LSI-R score is included in those data. However, as discussed in Chapter 4, the lack of attitudinal measures does not limit the applicability of the behavioral measures, which have been shown to be better predictors of peer influence in the criminological literature (Wellford, 1973; Warr & Stafford, 1991; Pratt et al., 2010).

A main limitation of the data: exclusivity to Pennsylvania. The incarceration and arrest histories pertain exclusively to the Commonwealth of Pennsylvania. The prior incarceration of a cellmate is indicative of his greater experience with the prison environment and greater experience with crime, more generally. Both are hypothesized to breed crime in the prison environment (Sutherland, 1947; Clemmer, 1950; Schrag, 1954; Mears et al., 2013). Cellmates who may have been incarcerated in other jurisdictions (i.e., other states, county jails) will be indicated as never having been incarcerated, even though they have prior experience with incarceration. If effects are criminogenic on average, their inclusion will bias those estimates toward zero. Similarly, the rearrest-based outcomes are measured using RAP sheet data that was sourced exclusively from

Pennsylvania. If the releasees were rearrested in other states and prison peer effects are determined to be criminogenic on average, the prison peer effect estimates will, again, be biased toward zero. More generally, the number of times an inmate had previously been arrested also reflects his criminal experience. Inmates who have committed additional crimes that were not detected by police will not be captured. Again, if effects are criminogenic on average, excluding those offenses will bias estimates toward zero.

Whether inmates appear to be differentially arrested, particularly in border counties, is an empirical question that was not addressed by the current study. However, a recent BJS report suggests that the bias due to missing arrests in other states will be small. The report indicated that only 10% of released prisoners were rearrested within five years in states other than the state in which they were released (Durose et al., 2014, p. 7). What percentage of those rearrestees was not also arrested in the state in which they were released was not reported. However, that a releasee who is still living in the state to which he was released would commit crimes exclusively in another state while not also committing them in his home state seems unlikely. In general, approximately 80% of Pennsylvania's inmates are released on parole, which means they must return to the jurisdictions from which they were committed (Pew Charitable Trusts, 2014). Among the first-time releasees in the 2006-2007 cohort, 85.67% (n=8,679) were released on parole.

In Summary

This chapter introduces a unique dataset to the criminological research community. Using administrative data from the Pennsylvania Department of Corrections and the Pennsylvania State Police, the current data were assembled and constructed. Never before has a dataset that reflects complete cellmate assignments for the entirety of prisoners' stays been constructed. The data include both correctional and arrest history data, which enriches the analyses possible from it beyond the capabilities of typical criminological data that are limited to correctional or arrestee samples. In addition to criminal history information, the data include all of the information (demographic and contextual) maintained by PADOC. While the data have some limitations, they represent the best currently available information on a cellmate sample from an adult prison population in the United States.

CHAPTER 7: A Formal Model for Recovering Treatment Effects under Essential Heterogeneity

This chapter follows Heckman and Vytlacil (1999, 2005), Heckman, Urzua, and Vytlacil (2006), and Basu, Heckman, Navarro, and Urzua (2007) to formally present the local instrumental variables method for estimating marginal treatment effect parameters and to explain how those parameters relate to other treatment effect parameters and the concept of essential heterogeneity. It assumes some basic calculus, econometric, and statistical knowledge. Full derivations are not presented in this chapter, as they can be referenced in the aforementioned articles.

A Basic Model Based on Potential Outcomes

In a potential outcomes (Fisher, 1935; Roy, 1951; Cox, 1958; Rubin, 1978) framework that assesses the role of a single treatment in producing two average outcomes, one for the treated individuals and one for the untreated individuals, the two potential outcomes can be denoted Y_{0i} and Y_{1i} . Those outcomes take the following forms:

$$Y_1 = \mu_1(X) + U_1 \; and \; Y_0 = \mu_0(X) + U_0 \qquad [9]$$

where characteristics X are observed by the researcher and the decision maker and characteristics U are certainly unobserved by the researcher, but may or may not be known to the decision maker. The fundamental problem of causal inference is that each individual can only assume one treatment value (Rubin, 1978). Randomization is intended to solve this fundamental problem (Fisher, 1935), as are statistical techniques that allow for causal inference, as described in Chapter 3 (Imbens & Angrist, 1994; Heckman & Vytlacil, 1999, 2005).

In this study, the outcome is reoffended (or not) and treatment is having spent a specific percentage (or more) of total prison stay time with a best cellmate. If $D_i = 0$ denotes the untreated case and $D_i = 1$ denotes the treated case, the realization of the outcome Y_i for each individual is:

$$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i} \tag{10}$$

Heckman and Vytlacil (1999) assume that a latent variable model determines the decision maker's treatment condition. Specifically, the latent variable D^* is assumed to take the form:

$$D_i^* = \mu_D(Z_i) - U_{Di},$$

$$where\ D_i = 1\ if D_i^* \geq 0\ and\ D_i = 0\ otherwise \tag{11}$$

In this case Z_i represents the observed and U_{Di} represents the unobserved random variables.

This is the basic model.

The basic model is based on the economic notion of utility whereby the underlying latent variable D_i^* represents the net benefit to the decision maker of choosing the treated state. D_i^* has an index structure and can take on multiple values, which translate to the treated condition above a threshold value and to the untreated condition below that threshold value, as will be described in more detail as the chapter proceeds. To make this more concrete for now, D_i^* might, for example, represent the potential amount or type of criminality-enhancing information that could be transferred from a cellmate to a releasee in a given amount of time. If the releasee suspects that that he can acquire more criminal skills from his cellmate, he may remain with his cellmate for a longer period of time, thereby enhancing the criminogenic effect of the association. As described in

Chapter 3, this basic model implies a two-step process. The first-step is a decision to be treated. That treatment decision leads to a second step in which the consequences of that decision are determined.

Identifying Assumptions

The local instrumental variables (LIV) framework of Heckman and Vytlacil (1999, 2005) requires that several identifying assumptions be imposed on the basic model. They are:

A1. Y_{0i} and Y_{1i} are defined for everyone. That is, there are realizations of outcomes stemming from both treatments in the study sample.

A2. Y_0 and Y_1 have finite first moments. That is, the expectations of Y_0 and Y_1 are well defined, meaning they have mean values.

A3. Y_{0i} and Y_{1i} are independent across decision makers, meaning the stable unit treatment value assumption (SUTVA) applies (Cox, 1958).

A4. $\mu_D(Z)$ is a nondegenerate random variable conditional on $X = x$, meaning, $\mu_D(Z)$ can take on more than one value, which determines treatment by virtue of its status as an exclusion restriction. This is one of Imbens and Angrist's (1994) instrumental variable assumptions: The instrument Z affects treatment D only through the endogenous regressor X.

A5. (U_D, U_0) and (U_D, U_1) are independent of (Z, X). This is the second instrumental variables assumption from Imbens and Angrist (1994), which states that the error terms (U) must be independent of the instrument, Z, and the endogenous regressor X.

A6. (U_D, U_0) and (U_D, U_1) are continuous with respect to Lebesgue measure on $\mathfrak{R}^2$.[28] This implies that U_D is distributed uniformly over the range between zero and one.

A7. $1 > Pr(D = 1|X) > 0.$, meaning the probability of being treated is well defined (i.e., there are both treated and untreated individuals in the study sample and the probability of treatment does not exceed one or fall below zero for any individual).

A8. $X_0 = X_1$ almost everywhere. That is, the treated and control groups are observationally equivalent (i.e., comparable), such that there is "common support of the propensity score" (e.g., Rosenbaum & Rubin, 1983, 1984; Apel & Sweeten, 2010b). The propensity score (i.e., propensity to be treated) defines to whom treatment effects apply. Common support of the propensity score means that for each propensity to be treated based on observables, there are people who both select into treatment and people who do not select into treatment.

Potential assumption violations: SUTVA. The assumption most likely to be violated in the current study is the stable unit treatment value assumption. SUTVA may be violated for two reasons. The first is that some releasees share the same longest-duration (i.e., most time-intensive) cellmate. The other, potentially more serious threat to

[28] A Lebesque measure is the notion of length extended to more complicated sets (e.g., beyond the distance between two points). That is, if length is the distance between two points, a and b, or b-a, a Lebesque measure extends that notion to multiple dimensions. This assumption is, as Heckman and Vytlacil (2005) put it, "a technical assumption made primarily for expositional convenience" (p. 676). It is akin to assuming continuity in two dimensions or over a plane, thereby allowing for integration.

the validity of the assumption, is that decisions regarding the length of cellmate associations do not rest exclusively with the releasee.

In the first-time release cohort under study, 17% (n=1,716) of the releasees share the same most stable, longest-duration cellmate. Therefore, the first releasee to have been treated by spending a particular amount of time with that cellmate could potentially influence the second releasee's treatment. However, as the discussion in the chapter to follow will indicate, while a releasee might enter into a cellmate relationship based on information about a cellmate, whether that relationship persists is more likely to be based on aspects of his particular relationship with his cellmate, rather than the prior relationship of his cellmate with another releasee.

The more serious potential SUTVA violation emerges from the nature of social interactions relative to the potential outcomes framework upon which LIV is based: they are not one-sided decisions. Social interactions necessarily take place between at least two people. In the current study, social interactions occur upon the pairing of a releasee with a cellmate. In the PADOC correctional system, how long that pairing endures may involve the agency of the releasee, the agency of his cellmate, the agency of both the releasee and his cellmate (e.g., via a cellmate request, as described in Chapter 5) or it may involve the agency of neither the releasee nor his cellmate: celling decisions may be completely attributable to correctional officer preferences.

To avoid SUTVA violations in the current application of the LIV method, the releasee alone is assumed to make the decision to remain with a cellmate. While this does not completely accord with the nature of socially-determined celling decisions that may potentially be made by the releasee, his cellmate, correctional officers, or some combination thereof, the LIV model allows for this departure from reality because it enables the characterization of the collective unobserved heterogeneity attributable to the preferences of each of the social actors. In the current application of the LIV method to social interaction effects, the preferences of the inmates and the correctional officers are unobserved. That is, the agency of the releasee, the agency of his cellmate, the agency of the correctional officers and, indeed, the agency of the broader correctional system that could be reflected in celling policies (e.g., maintaining minimum racial percentages per block, as reported in the bed assignment surveys that appear in the appendix to Chapter 5), are each unobserved determinants of the duration of cellmate association.

When treatment effects estimated via LIV are reported, they are reported with respect to the collective unobservables, which means that the unobserved determinants of the duration of cellmate association attributable to cellmate preferences, correctional officer and correctional system preferences, and releasee preferences are each lumped into a conglomerate measure of the potential variation in the social interaction effect estimates that results from essential heterogeneity. Moreover, the potential essential heterogeneity is not limited to only the unobservables related to the agency of the aforementioned actors: <u>all</u> unobserved factors are included the collective unobservables (e.g., inmate illnesses that result in their transfer, prison closings, etc.). Estimates reported with respect to the collective unobservables reflect their collective effect on outcomes, which limits the potential for inferences to be made based upon the unobserved information because it is impossible to know which of the unobserved factors (i.e., those attributable to unobserved releasee characteristics, unobserved cellmate characteristics, unobserved correctional officer characteristics, or other factors, such as the unobserved conditions of the cell) might be more or less critical to releasee outcomes.

Although this operationalization does not a perfectly reflect the processes that generate prison peer effects, neither does any empirical analysis based on the popular linear-in-means model, which implicitly makes the same assumption regarding a single decision maker (Durlauf & Ioannides, 2010; Sacerdote, 2014). This includes every prior empirical peer effect analysis in the criminological literature and most in the economic literature.

The current analysis improves upon prior analyses by taking the first step of applying the LIV model to estimate causal social interaction effects. Other methods do not eliminate bias due to essential heterogeneity nor do they characterize the contribution of the unobservables in any way. The LIV method does. Moreover, when the releasee is viewed as the decision maker and all other factors are unobserved: any given releasee's treatment (i.e., his longest-duration cellmate) does not affect the treatment of other releasees who are assigned to different time-intensive cellmates. SUTVA can hold.

The Propensity to Be Treated and the Propensity Not to Be Treated

Given the preceding assumptions, the propensity score or the probability of receiving treatment conditional on the instrument and other observables can be defined as:

$$P(z) = \Pr(D = 1|Z = z) = F_{U_D|X}(\mu_D(Z)) \qquad [12]$$

where F is the distribution of U_D conditional on X and $\mu_D(Z) = P(Z)$.

Recall equation [11] and note that it can be restated such that:

$$D^* = v(Z) - V \qquad [13]$$

where V is a continuous random variable that reflects the unknown determinants of the decision to be treated. This restatement of the determinants of treatment illuminates the relationships in [14]. The observed characteristics that determine the propensity score are a function of the instrument, whereas the unobservables are independent of it. The propensity not to be treated is, therefore, a function of the unobservables:

$$\mu_D(Z) = F_{V|X}\big(v(Z)\big) \text{ and } U_D = F_{V|X}(V) \quad [14]$$

Treatment Effects

In this section, the mean parameters that correspond to treatment effects relevant to the current study will be defined:[29] the average effect of treatment (ATE) parameter, local average effect of treatment (LATE) parameter, and the marginal effect of treatment (MTE) parameter, which is equivalent to the local instrumental variable (LIV) parameter.[30] To begin, note that the treatment effect for an individual decision maker i is $\Delta_i = Y_{1i} - Y_{0i}$.

Average treatment effect. This gain from treatment is comprised of two components: the average treatment effect (ATE) and unobserved heterogeneity. Following Heckman and Vytlacil (1999) and Basu et al. (2007) the average treatment effect is equal to:

$$ATE(X) = E(\Delta|X = x) = \mu_1(X) - \mu_0(X) \quad [15]$$

[29] For other treatment effect definitions and derivations of these parameters see Heckman & Vytlacil (1999, 2001, 2005).
[30] Heckman and Vytlacil (1999) framed the LIV method in terms of the LIV parameter, whereas Heckman and Vytlacil (2005) framed the LIV method in terms of the MTE parameter. The MTE parameter is preferable because it more clearly highlights the role that unobserved information plays in treatment decisions and their outcomes.

Unobserved heterogeneity is represented by $U_1 - U_0$ from the potential outcomes model. The ATE is the effect of treatment, averaged over all individuals in the sample.

Local average treatment effect. The local average treatment effect of Imbens and Angrist (1994) is defined as the effect of treatment on those who are induced to be treated by an arbitrary shift in the instrumental variable from z to z'. In this latent variable decision making framework, the instrumental variable is the propensity score $P(z)$ and the LATE is defined as:

$$LATE\left(x, P(z), P(z')\right) = \frac{E\left(Y \middle| X = x, P(Z) = P(z)\right) - E\left(Y \middle| X = x, P(Z) = P(z')\right)}{P(z) - P(z')}$$

where z and z' are realizations of Z for which $P(z) \neq P(z')$, which reduces to:

$$LATE\left(x, P(z), P(z')\right) = E(\Delta | X = x, P(z') \leq \overline{U}_D \leq P(z)) \quad [16]$$

where $\overline{U}_D$ is a probability transformation of U_D that results in the following uniform distribution: $\overline{U}_D = F_{U_D}(U_D)$

Local instrumental variables. The local instrumental variable (LIV) parameter is the limit of the LATE as $P(z) \rightarrow P(z')$. That is, LATEs apply over intervals, MTEs apply at points. As such the LIV parameter takes the form of a derivative, such that the LIV equals the derivative of the outcome with respect to the propensity score,

$$LIV\left(x, P(z)\right) = \frac{\partial E(Y | X = x, P(Z) = P(z))}{\partial P(z)}$$

which reduces to:

$$LIV\left(x, P(z)\right) = E(\Delta | X = x, \overline{U}_D = P(z)) \quad [17]$$

The observed aspects of the decision maker's treatment choice Z enter the calculus only through their index $\mu_D(z)$, which determines the propensity score. The Z then can be used to define the following probabilities, which clarify the relationship between the outcomes, the propensity score, and the observed and unobserved determinants of treatment.

$$\Pr(Y|X = x, Z = z, D = 1) = \Pr(Y|X = x, U_D \leq \mu_D(z)) \quad [17a]$$

$$\Pr(Y|X = x, Z = z, D = 0) = \Pr(Y|X = x, U_D > \mu_D(z)) \quad [17b]$$

$$and$$

$$\Pr(Y|X = x, U_D \leq \mu_D(z))) = \Pr(Y|X = x, \overline{U}_D \leq P(z)) \quad [17c]$$

$$\Pr\left(Y\middle|X = x, U_D > \mu_D(z)\right) = \Pr(Y|X = x, \overline{U}_D > P(z)) \quad [17d]$$

The preceding equations communicate the relationship between utility and the unobserved determinants of treatment ([17a-b]) and the relationship between the propensity to be treated and the unobserved determinants of treatment ([17c-d]). They are similar. When observed characteristics (or utility) are more important than unobserved characteristics to a treatment decision, individuals are treated, whereas when unknown factors are more important than known factors (or utility), individuals remain untreated.

Marginal treatment effects. The local instrumental variables concept (Heckman & Vytlacil, 1999) was a precursor to the concept of marginal treatment effects, as refined in Heckman and Vytlacil (2005) and more fully realized by Heckman et al. (2006). Unlike the parameters they had discussed in their 1999 article, Heckman and Vytlacil (2005) do not define the marginal treatment effect (MTE) parameter in terms of the propensity score. Instead they define the MTE as "the mean effect of treatment on those for whom $X = x$ and $U_D = u_D$" (Heckman & Vytlacil, 2005, p. 678). That is, for those whose realizations of observed and unobserved characteristics have specific values, the MTE is defined as:

$$MTE(x,u_D) = E(\Delta|X = x, U_D = u_D) \quad [18]$$

While this change in terminology and orientation is somewhat confusing, the MTE parameter is equivalent to the LIV parameter. The equivalency of the relationship between the MTE parameter and the LIV parameter is evident in equations [17c-d], which show the relationship between the propensity score and the unobserved determinants of a decision. It can also be derived as shown in Heckman et al. (2006, p. 397).

Relationship between the parameters. Heckman and Vytlacil (1999) show that "LIV defines the treatment effect more finely than do LATE, ATE, or TT," such that "[e]ach parameter is an average value of LIV, $E(\Delta|X = x, \overline{U}_D = u)$, but for values of U_D lying in different intervals" (p. 4731). In other words, MTEs are point estimates, whereas other treatment effects ordinarily are not.

Expressing the MTE in terms of X and u_D (instead of X and p, as in the LIV parameter) highlights the role of the unobservables in generating the MTE parameters. The other treatment parameters can then be expressed in terms of weighted integrals over the propensity score (from zero to one) of the MTE with respect to the unobservables (Heckman & Vytlacil, 2005, p. 680).

$$ATE(X) = \int_0^1 \Delta^{MTE}(x,u_D)\partial u_D \quad [19]$$

All other treatment parameters (except the LATE) are weighted versions of this relationship such that the weights are multiplied by the MTE, which implies that if $E(\Delta|X = x, U_D = u_D) = E(\Delta|X = x)$ and there is no unobserved heterogeneity, all treatment effect parameters will be the same. This is the only case in which a single, unique effect of treatment for all individuals can be identified (i.e., under response homogeneity).

To get the LATE, the MTE is integrated over the range u_D to $u_D{}'$:

$$LATE(X) = \frac{1}{u_D - u_D{}'} \int_{u_D}^{u_D{}'} \Delta^{MTE}(x, u_D)\partial u_D \qquad [20]$$

The contrast between the integration endpoints of the ATE and the LATE illustrates what Heckman and Vytlacil (1999) meant when they said the treatment parameters are interval dependent. In the case where the instrument is the propensity score, the MTE is integrated over the interval from zero to one to calculate the ATE, whereas is it is integrated over the interval $P(z) \geq 0$ to $P(z') \leq 1$ t to get the LATE. While the LATE could apply over the region between zero and one, it typically does not.

The relationship between MTEs and essential heterogeneity. As has been previously stated, essential heterogeneity is heterogeneity that results from some combination of selection on levels (unobservables) and selection on gains (outcomes). Estimating the marginal treatment effects tests for essential heterogeneity. If the MTEs are flat over an arbitrary interval with respect to the propensity score, there is no essential heterogeneity. If the MTEs are nonlinear with respect to the propensity score, essential heterogeneity is present (Heckman et al., 2006).

The importance of the propensity score. Heckman et al. (2006) argue convincingly for the importance of the propensity score as an instrument. Operationally, the propensity score, $P(Z)$, is an ideal instrument because it always produces positive weights for the MTE and the LATE, which is not necessarily the case when other instruments are used, as shown in Basu et al. (2007). Conceptually, the propensity score helps to highlight the influence of the observed and unobserved determinants of the treatment decision. For the observed aspects of the treatment decision, the propensity to be treated is can be estimated. As [17c] and [17d] show, the strength of the influence of the unobservables can then be ascertained by determining whether or not an individual is treated given his propensity to be treated. For well-defined questions, this allows the individuals to whom treatment effects apply to be identified based on their observed characteristics. This is a unique feature of the LIV method (Heckman et al., 2006; Heckman & Urzua, 2010).

Heckman and Urzua (2010) criticize ordinary instrumental variables methods for their failure to identify the portions of the populations to which LATEs apply beyond the broad statement that they apply to those who opt into treatment as a result of the manipulation of the instrument. In the LIV method, this population and its features can be identified via the propensity score, which is a summary measure that reflects the probability of selecting into treatment. While different levels of the covariates will generate different propensity scores, which makes it difficult to generalize broadly regarding the contribution of any single covariate to outcomes after treatment, if an individual's propensity to select into treatment based on observables can be identified and an MTE can be identified at that propensity score (i.e., there is common support) the treatment effects that apply to that individual can then be identified, as can the contributions made to those effects by each of the observed covariates and the collective unobserved information.

The importance of the validity of the choice model. The latent choice model for treatment is the first step relationship that generates the propensity score used as an instrument in the prediction of the outcome. The model characterizes the decision maker's treatment decision and, thus, deserves careful consideration: that decision making process must be well understood. (Hence, the condition that questions be well-posed.) Heckman et al. (2006) show that the choice model must be specified correctly to identify any treatment effects under conditions where essential heterogeneity is present. If the choice model is misspecified, the weights that need to be applied to MTEs to determine the various treatment parameters will be incorrect.

Correct specification of the choice model may seem like an impossible task that will circle inevitably back to the original problem of omitted variables bias in selection models (Imbens, 2009; Heckman & Urzua, 2010). However, as Basu et al. (2007) observed, while all available instruments should be included in the choice model, not all potential instruments need to be included. By "correctly specified," what is meant is that the unobservables U_D are independent of the instruments, Z, and the observed characteristics of the decision environment, X. That is, a potential instrument could be omitted, but as long as it is independent of the other instruments and $X's$, the consequence is only a loss of efficiency, not the introduction of bias (Basu et al., 2007, p. 1155).

Interpreting marginal treatment effects. Per Heckman and Vytlacil (1999, 2005) MTEs can be interpreted in three ways, which are equivalent as long as equation [11] holds, that is, as long as the choice model is valid. In the current study, the second interpretation is the focus because it highlights the unique ability of the LIV method to characterize the contribution of the unobservables to the outcomes.

1. $\Delta LIV(x,p)$ or $\Delta MTE(x,u)$ "is the average effect for people who are just indifferent between participation or not at the given value of the instrument (i.e., for people who are indifferent at $P(z) = p$)" (Heckman & Vytlacil, 1999, p. 4731), that is, "if they were exogenously assigned a value of Z, say z, such that $\mu_D(z) = u_d$" (Heckman & Vytlacil, 2005, p. 679). In other words, as if they were randomly assigned to treatment and control conditions, as described in Chapter 3.
2. $\Delta LIV(x,p)$ or $\Delta MTE(x,u)$ "for values of p close to zero is the average effect for individuals with unobservable characteristics that make them most inclined to participate" (Heckman & Vytlacil, 1999, pp. 4731-2) and "who would participate even if the mean scale utility $\mu_D(z)$ were small" (Heckman & Vytlacil, 2005, p. 679). Likewise, $\Delta LIV(x,p)$ or $\Delta MTE(x,u)$ "for values of p close to one is the average treatment effect for individuals with unobservable characteristics that make them the least inclined to participate" (Heckman & Vytlacil, 1999, p. 4732). "If U_D is large, $\mu_D(z)$ would have to be large to induce people to participate" (Heckman & Vytlacil, 2005, p. 679). In other words, the observed propensity to opt into treatment is balanced by the unobserved propensity to opt out of treatment.

3. "A third interpretation is that MTE conditions on X and the residual defined by subtracting the expectation of D^* from D^*[, such that] $\overline{U}_D = D^* - E(D^*|Z, X)$" (Heckman & Vytlacil, 2005, p. 679). In a linear regression framework, this is akin to writing $\varepsilon = y - \alpha - \beta$. The unobserved components of treatment are equal to the treatment minus the expected value of the treatment given the observed components of treatment.

Adaptation of the LIV Framework to the Study of Prison Peer Effects Moderated by Duration

The main difference between the current LIV implementation and the basic LIV framework outlined above is the addition of duration to the choice and outcome models such that the choice model [11] becomes [21] and the outcome model [10] becomes [22].

$$D_{it}^* = \mu_D(Z_{it}) - U_{Dit},$$
$$where\ D_{it} = 1\ if D_{it}^* \geq 0\ and\ D_{it} = 0\ otherwise \qquad [21]$$

In the current study, the addition of the temporal dependence is handled in an analytically simplistic manner: the LIV model is implemented for three duration thresholds, the choice of which is discussed in the following chapter. When considered in concert with each other, those three models allow for examination of the presence of temporal variation in average and marginal prison peer effect estimates.

$$Y_{it} = D_{it}Y_{1it} + (1 - D_{it})Y_{0it} \qquad [22]$$

In Summary

This chapter formally outlines the basic local instrumental variables framework, as exposited by Heckman and Vytlacil (1999, 2005). Limitations of the application of the

LIV method to the study of social interaction effects were discussed. A minor modification was made to allow for temporal variation in the prison peer effect estimates to be generated through an empirical application of this framework, which will be presented in Chapter 9. The current chapter is followed by Chapter 8, which lays the groundwork for the final LIV implementation. In Chapter 8, preliminary analyses are presented, the instruments are justified, potential duration thresholds are examined, and the presence of essential heterogeneity is established.

CHAPTER 8: Preparatory Analyses, Duration Thresholds, and Essential Heterogeneity

In hypothesizing that cellmates matter, such that social interactions with criminogenic cellmates will exert criminogenic prison peer effects that can explain some portion of the criminogenic effects observed several years after inmates are released from prison (Nagin et al., 2009), the current study relies on Sutherland's (1947) differential association theory and developmental cascades (Masten et al., 2005). Potentially criminogenic cellmates are cellmates who, based on their past offending behavior and other life outcomes (e.g., education, substance abuse), appear to have more criminal experience and the criminal attitudes and skills (i.e., criminality) that are consistent with more criminal experience. Levels of criminal experience and criminality are indicated by the number of prior arrests and the risk assessment scores of the Pennsylvania Department of Corrections (PADOC) first-time releasees and their cellmates and, for the cellmates, by whether they have a prior incarceration. Per balance theory, relative distances between the criminal experience and criminality of releasees and their cellmates are expected to moderate the relationship between criminogenic cellmates and reoffending (McGloin, 2009).

Overview of the Current Chapter

The current chapter presents preliminary analyses that lay the groundwork for the final local instrumental variables (LIV) model to be presented in Chapter 9. Linear probability models (LPM) for the choice and outcome models are discussed. The instrumental variables are justified conceptually and empirically, through LPM and instrumental variables (IV) specifications. Duration thresholds are explored via IV methods. Finally, the presence of essential heterogeneity is established via Heckman et al.'s (2006) test for it. These analyses demonstrate that prison peer effects on reoffending have the potential to emerge through cellmate associations and delineate when in the development of those associations those effects might become detectable. Prison peer effects are not estimated in this chapter, which presents only preliminary analyses. The final analyses that estimate prison peer effects are presented in Chapter 9.

Linear probability model specifications. As described in Chapters 4 and 7, the LIV model is comprised of two equations: a choice model and an outcome model. The choice model estimates the propensity for releasees to remain in cellmate associations over time. The outcome model estimates the effect of those choices on releasees' reoffending outcomes, rearrest and more general recidivism, which is defined as rearrest or reincarceration without rearrest. In the current chapter, those models are outlined and justified, beginning with simple linear probability model specifications for both the choice and outcome models.

Linear probability models are the baseline specifications upon which the instrumental variables and local instrumental variables specifications are built. While they do not address selection or apply to dichotomous outcomes, LPMs are illustrative of whether the theoretically expected relationships might emerge: they can establish whether there is likely to be an association between reoffending and duration of association. Additionally, they can demonstrate how well the data predict the duration of cellmate associations. They further allow for a quick verification that prospective exclusion restrictions predict the duration of cellmate associations, but do not predict reoffending. They may also highlight other potential exclusion restrictions and reveal the presence of significant predictors of reoffending other than the social interaction variables (prior arrest, prior incarceration, and risk scores) of primary interest. Finally, in comparison with results from instrumental variables and local instrumental variables (LIV) specifications, LPMs illustrate the effect that biases due to unobserved and essential heterogeneity have on effect estimates.

Instrumental variables specifications. After the relationships between the primary dependent and independent variables and the covariates are explored via the LPM specifications, bias due to unobserved heterogeneity, or selection on levels, in the relationship between cellmate social interactions and reoffending is addressed through instrumental variables models, including two-stage least squares (Imbens & Angrist, 1994) and Stata's *ivprobit* routine. The means through which instrumental variables isolate effects, even in the presence of unobserved heterogeneity, was discussed thoroughly in Chapter 3, so only the 2SLS and *ivprobit* instrumental variables implementations are presented in this chapter. Through the IV implementations, the conceptual and statistical validity of the exclusion restrictions is established. After initial IV models are estimated, the potential for variation in duration of cellmate associations to differentially impact releasees, both alone and in relation to the timing of the pairing relative to the releasee's stay, is assessed.

The role of duration. The duration of cellmate associations is expected to delineate the temporal regions in which prison peer effects might arise, as well as to moderate them. A continuous operationalization of duration, such as *ivprobit* requires and that has been applied previously in the criminological literature (e.g., Warr, 1993; Haynie et al., 2005), assumes that each additional day spent with a cellmate will impact a releasee similarly.

While Sutherland (1947) and Clemmer (1940) predicted a positive relationship between duration of association and peer influence, prior prison studies and balance theory suggest that the relationship between duration and prison peer effects might be nonlinear (Wheeler, 1961; Garabedian, 1963; Wellford, 1967; McGloin, 2009). Cellmate associations may take some time to develop and to exert prison peer effects because cellmate associations are often nascent, not established, social relationships. Moreover, even if cellmates have a prior social relationship (e.g., on the cellblock or in a job assignment), living in close quarters with that person, which brings its own unique challenges (Becker, 1974; Schwartz, 2013), is at the very least a new stage of that association. As prison peer associations evolve, prison peer effects may also dwindle due to anticipatory socialization effects as inmates approach their release dates (Merton, 1957; Wheeler, 1961) or they may dwindle as a function of tendencies toward balance in associations (McGloin, 2009).

The presence of essential heterogeneity. To determine whether prison peer effects take some time to emerge from newly-established cellmate associations and to determine whether they relate nonlinearly to the duration of cellmate association, successive thresholds of that duration are explored through LPM and 2SLS analyses. The duration of cellmate association is not shown to be significant at any threshold in any model of rearrest. However, for some duration thresholds the effect of duration on recidivism is significant or and pointing consistently in the criminogenic direction. This variation in outcomes at different duration thresholds suggests that the average treatment effect estimated via the *ivprobit* routine may not appropriately characterize marginal prison peer effects with respect to time, even though *ivprobit* accurately models a dichotomous outcome affected by a continuous treatment (Nichols, 2011).

To see if essential heterogeneity is present, Heckman, et al.'s (2006) test for essential heterogeneity is applied at each duration threshold. Those tests reveal the presence of essential heterogeneity and dictate the implementation of a method that can control for it. To that end, Heckman and Vytlacil's (1999, 2005) method of local instrumental variables (LIV) will be described and implemented in Chapter 9. That LIV implementation will provide an answer to the question of whether cellmates matter in the production of reoffending.

The Choice and Outcome Models

To initially examine whether criminogenic cellmates might affect the reoffending outcomes of a first-time PADOC release cohort and whether the duration of cellmate association can be predicted using the potential exclusion restrictions described in Chapter 6, it is useful to estimate linear probability models for the choice and outcome models. LPMs are ordinary least squares regressions applied to dichotomous outcomes. Although biased due to the functional form incompatibility, linear probability models are easy to implement and to interpret (Long, 1997; Angrist & Pischke, 2009; Chesher, 2010). They therefore allow for a quick demonstration that a relationship between reoffending and the duration of cellmate association exists, is likely to be robust to specification, and that the duration of cellmate association can itself be predicted with variables other than those used to predict reoffending (i.e., that exclusion restrictions exist).

Five linear probability models, one for the choice model (days spent with cellmate) and two for each outcome, rearrest and recidivism, are estimated. Variables related to releasees, cellmates, criminal experience and criminality (i.e., social interaction variables), cellmate pools, other cellmate association and prison context factors, releasee-cellmate homophily, PADOC facility fixed effects, and the potential instruments are added to each of the five model in succession.[31] For descriptions of these variables and why they are relevant to the study of prison peer effects please see Chapters 2, 4, and 6. The LPM specifications, which are estimated with *regress* in Stata, appear in Figure 3.

To preserve temporal order, the choice model does not include cellmate pool variables because all members of the pool had not yet been encountered prior to the releasee-cellmate pairing. The choice model also does not include releasee level or relative risk scores. Risk scores are primarily used by the correctional system, so there is no reason to assume inmates are aware of their own risk scores or the risk scores of other inmates. What inmates are potentially aware of, however, are the observable constituent elements of those risk scores, such as other inmates' approximate ages and whether they are attending prison-based GED classes or substance abuse counseling. Moreover, through conversation, inmates may quickly become aware of additional constituent risk score elements, such as other inmates' criminal experiences (e.g., approximate number of prior arrests, prior misconduct offenses, and prior parole violations) over time (e.g.,

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[31] In response to the claim by correctional officers that sections have their own cultures, section level fixed effects were also estimated. However, because there are so many sections (n=400), some of which have few observations, partitioning the sample to this degree did not prove fruitful. Some sections had too few releasees. The same held true for building (n=195) level effects. Therefore, given the uneven distribution of the releasees across buildings and sections, the cellmate pool characteristics are the measures best suited to serve as the most proximal indicators of peer group effects on reoffending.

Clemmer, 1940; Sutherland & Cressey, 1955; Shaw, 1966; Earley, 2000; Jones & Schmid, 2000; Santos, 2006; Attwood, 2014).

Two sets of outcome models are estimated as a function of the choice model. Outcome model #1 includes only prior incarceration and prior arrest social interaction variables along with all of the covariates. Outcome model #2 adds the risk score variables, the releasees' risk scores and the relative release-cellmate risk scores, to the model. Each model is estimated once for each reoffending outcome: rearrest and recidivism. Each of these models is imperfect, but for different reasons.

*** [Figure 3 here] ***

The first model is complete in that each of the covariates, aside from the exclusion restrictions and the risk scores, factor into both the choice and outcome models. However, the omission of the risk score means that comparisons cannot be drawn between the criminal experience and the criminality measures within the context of the same model. While the second model allows for those comparisons, it also introduces collinearity because each of the constituent elements of the risk score is included as independent covariate in the outcome model.

The continuous constituent risk score covariates, age and prior arrest, factor into the risk score categorically, so they enter the LPM model differently as a function of the risk score. The dichotomous constituent risk score covariates, on the other hand, factor into the risk score also as dichotomous indicators. While the dichotomous elements of the risk score, like their continuous counterparts, enter the outcome model differently as a function of the risk score, they are also more directly correlated with it than are the continuous age and prior arrest measures. Nevertheless, eliminating the constituent covariates of the risk score proved to be neither theoretically nor methodologically sound, as described in the footnote. Each was, therefore, left in the second outcome model. The two models are presented in conjunction with each other for completeness and because neither is a perfect specification.[32]

Likelihood ratio tests were used to evaluate whether each of the groups of variables jointly and significantly improved upon the prior group of variables (e.g., whether cellmate characteristics improved upon releasee characteristics; whether pool characteristics improved upon releasee and cellmate characteristics; and so forth). The results of the likelihood ratio tests and significance tests for each of the sets of models are presented in Table 7. Gray boxes indicate significant ($p<=0.05$) likelihood ratio tests (groups of variables) or significance tests (single variables). White boxes indicate

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[32] Outcome models that eliminated all variables constituent to the RST score were also estimated. Those models clearly did not characterize the hypothesized relationships. When the constituent elements of the RST score (e.g., age, age of first arrest, prior arrests, parole violations, high school completion, misconducts, and drug use) were removed from the outcome models, variables that had never before been significant to those models (e.g., the instruments, homophily variables, facility fixed effects, and less important characteristics such as military service record) became significant as variation in the remaining, previously less critical, variables was inappropriately leveraged to replace the lost variation. This suggests that the RST score as a summary measure cannot substitute for its constituent elements.

It was initially hypothesized that this perturbation was largely driven by the omission of the two non-dichotomous risk score elements, age and prior arrest, which are both highly correlated (theoretically and methodologically) with the outcomes. To test that hypothesis, models that eliminated one of the two were estimated. Eliminating either age or prior arrest causes the same type of perversion with respect to the other variables in the model (i.e., they carried inordinate weight). Including both seemed to eliminate it.

Models that included prior arrest and age, but excluded the dichotomous elements of the risk score were then estimated. However, in instrumental variables specifications (e.g., *ivreg2* and *ivprobit*) the dichotomous variables, which are treated as instruments if included in the choice equation, but eliminated from the outcome equation, proved relevant to the outcome model (i.e., they failed the Sargan-Hansen test). Moreover, there is no theoretical reason to assume that the constituent elements of the risk score will not have independent effects on the outcome. The decision was, therefore, made to include all constituent elements of the risk score in the outcome equation.

insignificance. Crosshatched boxes indicate that the variables were not included in the model. Only the estimates and p-values for duration of cellmate association are reported. Full output from the choice and both sets of outcome models appears in the appendix associated with this chapter. The LPMs are, again, simply meant to be instructive insofar as the formulation of the choice and outcome models is concerned, so the results from these regressions are discussed only in the context of what they mean for later analyses.

*** [Table 7 here] ***

Explained variance. Collectively, these models explain 43.38% of the variance in duration, but only about 20% of the variation in rearrest and only about 18% of the variation in any available official measure of recidivism. That the outcome models are able to explain approximately 18% of the variance in reoffending outcomes is encouraging, given that most criminological studies are not able to explain more than 10% of the variance in criminal behavior (Weisburd & Piquero, 2008).

Joint significance tests. The results presented in Table 7 indicate that each of the included variable groups (i.e., not the cellmate pool) is jointly significant to the choice model. Across the specifications, the releasee, cellmate, cellmate pool, other, and social interaction characteristics are also jointly significant to the rearrest and any recidivism outcomes. The potential exclusion restriction variables are jointly insignificant to both outcome models, which suggests that they are good instruments. Additionally, both the facility fixed effects, which are jointly significant only to recidivism, and the homophily variables, which are jointly significant only to rearrest, might also be good exclusion restrictions in the instrumental variables specifications, even as they indicate differences in the etiology of rearrest and recidivism, which will be discussed later in this chapter and in Chapter 10.

Duration of association. Across models, the average effect of time spent with a single cellmate is small and crimino-suppressive, but only significant (p_1=0.01, p_2=0.01) for the any recidivism models and the first rearrest model and not significant for the second rearrest model (p_1=0.05; p_2=0.7), which suggests differences in the etiology of rearrest versus recidivism. This is entirely plausible, given that social interaction effects are known to be highly context and outcome dependent (Hartup, 2005; Brechwald & Prinstein, 2011; Horney et al., 2012; Sacerdote, 2014) and that the processes involved in generating rearrest and reincarceration are likely to be different (Useem & Piehl, 2007; Raphael & Stoll, 2009; Grattet et al., 2009, 2011; NRC, 2014). However, it is troubling that prison peer effects would be so sensitive to the choice of outcome, particularly when the outcomes are both related to criminal activity and detection of that activity by the criminal justice system. Moreover, it suggests that the significant and marginally significant effects in the recidivism models are likely to be driven by less than 10% of the releasees (n=877), who were reincarcerated, but not arrested.

Social interaction variables. Statistical models can include either releasee and cellmate absolute (i.e., level) measures or a releasee level measure and a releasee-cellmate relative measure. Due to collinearity, the relative measure and the level cellmate measure cannot both be included in the same model. Therefore, the choice was made to comport with the prior work of McGloin (2009) to assess whether the relative distance between the releasee and his cellmate matters.

As opposed to level measures, relative measures allow for a more nuanced interpretation regarding the effect of a cellmate on his releasee because they reflect which of the inmates is more criminally-inclined, based on observable information. Per balance theory, more criminally-involved cellmates and cellmates with more criminality should have criminogenic effects on releasees, whereas releasees who are more criminally-involved or who have more criminality than their cellmates should experience crimino-suppressive effects as a result of prison peer influence. As outlined in Chapter 6, the relative measures in the current study reflect relative risk scores and relative prior arrests. Releasee level measures are subtracted from cellmate level measures so that positive relative values indicate that the cellmate is more criminal (i.e., has more criminal experience or more observed criminality) than the releasee and negative relative values indicate that the releasee is more criminal than the cellmate.[33]

On average, the relative criminality and criminal experience measures do not appear to directly impact releasees' reoffending outcomes, either rearrest or general recidivism, over and above the releasees' levels of criminal experience and criminality, which do have direct effects on both reoffending measures. However, the relative prior arrest measure does appear to impact releasees' outcomes indirectly through the influence of the duration of cellmate association. The association of relative cellmate and releasee

[33] It should be noted that although these measures comport with prior criminological research (McGloin, 2009), difference scores are not the preferred measures to assess congruence. They are a special case of polynomial regression, which is the preferred method (Edwards, 2001). However, the purpose of the current study is not to assess congruence. In fact, as was discussed in Chapter 4, the cellmates' outcomes are not fully known, so the current study cannot assess congruence. A more relevant shortcoming of these relative measures is that they assume that relative distances have the same impact, no matter where they occur. That is, they assume homogeneity across the continuum. This assumption is unlikely to be valid. For example, a relative distance of two prior arrests at one arrest versus three arrests might be quite different than a difference of two prior arrests at eight and ten arrests (e.g., Blumstein et al., 1986).

prior arrest with the duration of cellmate association is suggestive that inmates may choose to associate with each other for longer or shorter periods based on their criminal experiences.

Potential instrumental variables. Three potential instrumental variables are examined: first post-initial classification (IC) cell square footage, first post-IC cell tier, and cellmate's time served before pairing. Cell tier significantly predicts rearrest and is marginally significant for any recidivism in one of the models, so it cannot serve as an instrument. Neither of the remaining potential instruments is a significant predictor in any outcome model, but each is a significant predictor in the choice model, which suggests that both have the potential to be good exclusion restrictions. Statistical tests, which are presented later in this chapter, demonstrate can demonstrate the empirical validity of the instruments. However, instrumental variables must be justified conceptually as well as statistically (Imbens & Angrist, 1994; Bushway & Apel, 2010).

Can the instruments be justified conceptually? Although results from the linear probability models estimated above show that the instrumental variables (square footage of the first assigned cell and cellmate's time served prior to pairing) appear to be exogenous to the outcome model, they must be justified conceptually. After initial classification, inmates are sent to their first permanent facility within the PADOC system. Once assigned to a facility, placement in a cell is random after a few observable characteristics are taken into consideration. Per Chapter 5, those factors are, most notably, race and medical limitations.[34] Characteristics of the first post-IC cell environment and the timing of the move relative to the cellmate are, therefore, potentially exogenous instruments. The main assumption (Imbens & Angrist, 1994) that those exclusion restrictions must meet is that a cellmate's time in prison can only affect the releasee through his pairing with that cellmate. Likewise, the physical environment of a particular cell should only affect a releasee if he is placed in that cell.

While it might be argued that inmates are often rewarded with moves to preferred cells, which could be larger cells, or preferred cellmates, who might be capable of more stable, time-intensive associations, this argument does not reasonably apply to inmates who are experiencing their first placement in a facility. While they may have been assigned high or low custody levels based primarily on their criminal histories, at the time of their initial post-IC placement inmates have not yet had the opportunity to demonstrate positive adjustment (i.e., that they will do "good time'), which might be rewarded (Adams, 1992; O'Hear, 2012). Nor are they likely to have demonstrated the potential for negative adjustment (i.e., troublemaking), which might increase their potential to be assigned to a smaller cell or to a more acerbic cellmate. Moreover, by their own admission, correctional officers know very little about incoming inmates (personal communication, 2013), as is illustrated by the celling checklist employed at SCI-Pittsburgh, which appears in the appendix to Chapter 5.

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[34] Correctional officers also list similar age as a factor, but this is not evident in the data. See Chapter 3 for a description of the process that correctional officers use to assign inmates to cells.

In addition to the paucity of information they have about incoming inmates, the decisions correctional officers make regarding initial cell assignments are generally constrained by factors other than the characteristics of the inmates and their cells. Table 2 shows that nearly all PADOC SCIs operated above capacity between January 1, 2000 and December 31, 2007, a situation that served to constrain correctional officer's discretion in making cell assignments. More compelling is the information provided by the bed assignment surveys. In response to the bed assignment survey, no correctional officers reported that initial placements are based on cell size characteristics or a cellmate's time served, despite the fact that they reported nearly fifty other unique criteria for celling inmates, as shown in the appendix to Chapter 5.

On the use of multiple instruments. Basu et al. (2007) write, "If there are multiple instruments which have been proven to be significant determinants of the choice of treatment, then all of them should be simultaneously included in the estimation of the choice model" (p. 1155). This is because different instruments estimate different treatment effect parameters. Treatment effect estimates are sensitive to the choice of instrument (Imbens & Angrist, 1994; Bushway & Apel, 2010; Heckman et al., 2006; Basu et al., 2007). This sensitivity remains even when the propensity score is used to predict the outcome, as Basu et al. (2007) illustrate in their analysis of breast cancer treatment outcomes in which they compared the estimates from two exclusion restrictions. The effect estimates stemming from both were correct, but incomplete, meaning they each applied only to a portion of the sample. When combined, they provided a more accurate illustration of the determinants of treatment and outcomes.

The current study seeks to estimate treatment effects that are not sensitive to the choice of instrument (e.g., Heckman & Urzua, 2010), so multiple exclusion restrictions are used to specify the choice model. Moreover, the instruments chosen, particularly the facility fixed effects (described below), cover the full range of observations, meaning the estimates generated through employment of those instruments can generalize to the entire sample, as opposed to only to specific individuals in the sample (e.g., Bushway & Apel, 2010).

Facility fixed effects. Facility fixed effects are collectively insignificant to the production of rearrest, but appear to jointly affect any recidivism. However, only SCI-Mercer is a significant predictor on its own. The lack of a significant relationship between reoffending and every other facility, particularly given the facilities' differing security levels, may be surprising given the prior literature related to the prison context which found that assignment to higher security level facilities increased recidivism (Gaes & Camp, 2009). However, the lack of concordance between the current study and previous studies may also be purely contextual, as peer effects have been shown to vary considerably depending on the domain in which they are measured (Brechwald & Prinstein, 2011; Hartup, 2005; Sacerdote, 2014).

PADOC is currently studying how facility assignments are made in order to improve inmate placement, which suggests that the disparity between the current findings and the extant literature may reflect organizational differences between the state correctional systems in Pennsylvania and California, the system Gaes and Camp (2009) studied. In the PADOC system, inmates of varying custody levels are dispersed throughout the system, whereas the classification and placement system used in

California is more formulaic and, therefore, potentially better suited to evince facility-level differences in inmates' post-release reoffending outcomes that result from it (Berk & de Leeuw, 1999; Tahamont, 2013). Alternatively, it may just be that the facilities matter differently than has previously been imagined. Specifically, it appears that facility assignments impact rearrest through the amount of time releasees spend with their cellmates.

> *"`The reason [cellmates] are allowed to cell together is because I believe in putting people into cells who are compatible,' [Matthews, the warden at Leavenworth] said" (Earley, 2000, p. 256).*

Facility level effects might directly predict the duration of cellmate relationships because different institutions may have different administrative preferences and process related to the celling of inmates. At SCI-Dallas and SCI-Pittsburgh, for example, some correctional officers expressed a preference for disallowing convenience moves, whereas others, like Matthews, believed that convenience moves helped to maintain institutional harmony (personal communication, 2013). Similarly, some facility superintendents might look favorably on convenience moves and cellmate requests, whereas another may not. As seems to have been the case in Leavenworth, the personal preference of the superintendent may then become an institutional preference, particularly if the superintendent uses his authority to enforce that preference via administrative rules (e.g., Diulio, 1987; Wilson, 1989).

Homophily variables. Individuals tend to associate with other individuals similar to themselves. This tendency toward what sociologists call homophily is one of the most robust findings in the criminological, sociological, psychological, and economic literatures (Glueck & Glueck, 1950; Gans, 1961; Cohen, 1977; Kandel, 1978; Buss, 1985; Mortensen, 1988; Warr, 2002; Weerman & Smeenk, 2005; Currarini, Jackson, & Pin, 2009; Young, 2011; Schwartz, 2013). As shown in Table 6, cellmate associations conform to this general tendency.

Although cellmate relationships, like all human relationships, exhibit homophily across multiple demographic and criminal history characteristics, not all of the homophily variables appear to impact reoffending. Only prior employment, urbanity, mental health problems, and religion appear to affect reoffending. Moreover, only for the rearrest outcomes are the homophily variables collectively significant to the releasees' propensities to reoffend. In contrast, like facility assignment, sameness between inmate pairs does appear to consistently play an indirect role in both rearrest and recidivism outcomes by helping to determine how long cellmate associations persist. These relationships make sense in the context of the extant literature, which has found that relationships between more similar couples last longer (Schwartz, 2013). Thus, there is reason to expect similarity between cellmates to predict relationship duration, even if it does not affect rearrest (e.g., Mortensen, 1988). However, the preliminary linear probability models also suggests that the homophily variables might not serve well as valid instruments because several of them significantly affect both reoffending outcomes, holding all other variables constant, even though they do so jointly only for rearrest.

Insignificant outcome predictors. Aside from the joint significance of classes of variables, the standard errors for the coefficients on individual variables estimated via the linear probability models suggest that some of them do not belong in the outcome models because they indicate a failure to reject the null hypothesis that those variables affect duration, rearrest, or recidivism. While those models could be refined to eliminate those variables, doing that would eliminate many variables that criminological theory expects to affect these outcomes, per the discussions in Chapters 2, 3, and 6. They are, therefore, left in the models. Only those groups of variables that appear to be good potential instruments (e.g., facility fixed effects and instrumental variables) due to their failure to jointly affect the reoffending outcomes are eliminated from the outcome models. They are still included in the choice model.

A More Appropriate Model to Estimate Causal Effects: Instrumental Variables

According to Long (1997), linear probability models are inappropriate for dichotomous outcomes for several reasons, the most important of which is that they violate the functional form (i.e., normality) assumption of ordinary least squares. Further, in contrast to the examples presented by Angrist and Pischke (2009) to validate the practice of estimating LPMs, Dong and Lewbel (2012) showed that in some circumstances linear probability models failed to predict even the correct sign of the average treatment effects estimated. Therefore, the relationship between rearrest and time spent with cellmates should be demonstrated to be robust to proper specification using an appropriate model, such as the probit model.

Although more appropriate to dichotomous outcomes, the probit model, like the LPM, assumes that no omitted variables bias the estimates of the effect of social interactions with cellmates on rearrest. That is, probit and OLS implausibly assume an exogenous relationship between the explanatory variables and the error term in the production of rearrest and recidivism. As explained in detail in Chapters 2, 3, and 4, the duration of the cellmate association is likely to be endogenous because many unmeasured characteristics of the releasees, their cellmates, and their institutional environments might influence both how long releasees remain in cellmate relationships and whether they reoffend.

Two-stage least squares (2SLS) is one approach to estimating treatment effects free of unobserved heterogeneity. It is also the most common method used for estimating instrumental variables models (Imbens & Angrist, 1994; Nichols, 2007, 2011; Angrist & Pischke, 2009). As the name implies, it involves two steps. In the first step, the exclusion restrictions are used to predict variation in the endogenous explanatory variable via ordinary least squares (OLS) regression. The second step is also an OLS regression in which the outcome is regressed on the predicted endogenous variable in order to arrive at the instrumented estimate of the average effect of the endogenous variable on the outcome. As just discussed, OLS is inappropriate for dichotomous outcomes, so 2SLS is an inappropriate model in the current framework. Its virtue lies in its ability to test the validity of the instruments. Stata's *ivreg2* routine implements 2SLS and reports the results from three tests of the exclusion restrictions.

Stata's *ivprobit* routine estimates effects for models with dichotomous outcomes and continuous treatments, which are thought to be subject to unobserved heterogeneity. Unlike *ivreg2*, the *ivprobit* routine is appropriate for estimating an average treatment effect (ATE) when outcomes are dichotomous and the endogenous regressor is continuous (Nichols, 2007, 2011). *ivprobit* is, therefore, an appropriate estimation strategy under the current conditions, wherein the outcome variables, rearrest and recidivism, are dichotomous and endogenous regressor, the number of days spent with a cellmate, is continuous. However, unlike the *ivreg2* routine, the *ivprobit* routine reports scant tests for the validity of the instruments (Baum, Schaffer, & Stillman, 2007).

Using Stata's *ivreg2* routine, models were estimated including the instrumental variables (cell square footage and cellmate's time to releasee), the homophily variables, and the facility fixed effects. Those models did not pass the validity tests (results not shown). The *ivreg2* and *ivprobit* models were then re-estimated without the homophily variables. The results from the tests of the exclusion restrictions from *ivreg2* are presented in Table 8. The results from *ivprobit* are presented in Table 9. For *ivreg2, o*nly the results of the tests of the exclusion restrictions are discussed, whereas the *ivprobit* results are discussed only in the context of the duration and social interaction variables.

*** [Table 8 here] ***

Do the instruments pass the validity tests? *ivreg2* reports the results of several tests of the validity and strength of the instruments: an underidentification test, a weak identification test, and the Sargan-Hansen test for the joint validity of the instruments (Baum, et al., 2007).[35] The choice model for both the rearrest and recidivism outcomes is the same, so each of the tests applies to both models. To summarize, the results from each of the three tests of the exclusion restrictions, presented in Table 8, indicates that, collectively, the instruments are both valid (e.g., related to the outcome only through the

[35] When errors are heteroskedastic, the tests of the validity and strength of the instruments may be invalid because instruments can present as valid, even when they are not. Analogous tests to the ones described in the main text are performed automatically if the *robust* option is specified to handle heterskedasticity. The robust option was specified in each of the *ivreg2* models.

endogenous regressor) and strong predictors of the endogenous regressor, duration of cellmate association.

The underidentification test. The underidentification test reports a test of the rank of the matrix of coefficients and instruments. The null hypothesis is that the matrix is not full rank (i.e., the rows and columns are not linearly independent), meaning that the model is not identified. A rejection of the null hypothesis means that the model is identified. The significant chi-square statistics associated with the identification tests indicate that, for all four specifications, the model is identified.

The weak identification test. Bound, Jaeger, and Baker (1995) showed that identification is not possible when the instruments are only weakly correlated with the endogenous regressor. The intuition behind their result is that if only a tiny amount of exogenous variation is leveraged, the chance of detecting differences in outcomes as a result of that miniscule amount variation erodes quickly, particularly in smaller samples. The test for weak instruments employed by *ivreg2* is a version of the Cragg-Donald test, which identifies the least partial correlation between the endogenous regressor and the instruments (i.e., the minimum eigenvalue is identified). To assess whether the instruments are weak relative to the amount of bias to be tolerated, the Cragg-Donald statistic should be compared to the critical values derived by Stock and Yogo (2005). For each specification, the Cragg-Donald statistic is larger than the Stock-Yogo critical value at 5% bias, which suggests that the instruments are not weak. Were the Stock-Yogo critical value above the Cragg-Donald F-statistic, the instruments would be considered weak.

The Sargan-Hansen test. The Sargan-Hansen test assesses the joint null hypothesis that the instruments are valid instruments, in the sense that they are related to the outcome only through the endogenous regressor(s). Rejection of the null indicates that the instruments may not be valid instrument because they appear to belong in the second-stage outcome equation as well as in the first-stage choice equation. In the current analyses, the insignificant chi-squared statistics indicate a failure to reject the null hypothesis that the instruments are valid.

*** [Table 9 here] ***

Interpreting the *ivprobit* results. Although *ivreg2* reports tests of the instruments that are valid under homogeneity, per the discussion above, the *ivreg2* estimates are biased due to the functional form incompatibility, whereas the results from the *ivprobit* analysis are not. Results from the *ivprobit* analysis appear in Table 9.

Duration. For rearrest the duration of cellmate association is not significant in either the first or the second outcome models (p_1=0.365; p_2=0.559), nor in the second any recidivism model. Duration was significant in the first model for any recidivism (p_1=0.028; p_2=0.060). These results suggest that considerable unobserved heterogeneity had biased the previous LPM estimates. The significance of the estimated effects was reduced dramatically in IV estimates, as compared to the LPM estimates. More importantly, even though they are imprecisely estimated, the direction of the effects appears to have shifted from crimino-suppressive in the LPM models to criminogenic in the IV models.

Social interaction variables. The relative prior arrest and relative risk score measures are not significant predictors of rearrest or recidivism in either outcome model, but the level measures for both releasee prior arrests and releasee risk scores are significant for both rearrest and any recidivism in each of the models.[36] Neither is cellmate prior incarceration. Only the release prior arrests and risk scores are significant predictors. Each significantly predicts both reoffending outcomes.

Relationship timing. Finally, the timing of the pairing of the releasees and their longest-duration cellmates appears inconsequential with respect to the releasees' rearrest outcomes. Prior criminological research suggested that inmates might become less prisonized as their release dates approach and they begin to orient themselves to less criminal reference groups outside prison (Merton, 1957; Wheeler, 1961; Glaser & Stratton, 1961). This suggests that cellmates encountered closer to releasees' release dates might engender weaker prison peer effects, as the findings from prior studies of prisonization had indicated (Wheeler, 1961; Garabedian, 1963; Wellford, 1967). In contrast to that prior research, the coefficients on the releasee time to release measure were imprecisely estimated in each of the rearrest models currently under consideration, which fails to indicate that the timing of the releasee-cellmate pairings mattered. In the recidivism models, however, the releasee's time to release at pairing with his longest-

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[36] To investigate the possibility that the level cellmate prior arrest and risk scores measures would significantly predict releasee outcomes, each of the models (the choice and four outcome models) was re-specified such that the level measures replaced the relative measures. The cellmate level measures were also insignificant predictors of release reoffending. To investigate further, interaction terms (e.g., releasee prior arrests x cellmate prior arrests; releasee risk score x cellmate risk score) were also added to these models. Again, neither the cellmate level nor the interaction terms emerged as significant predictors of releasee reoffending. Only the releasees' prior criminal experience predicted their reoffending.

duration cellmate did emerge as a significant (p<=0.05) predictor in both models. This result continues to indicate differences in the etiology of rearrest and reincarceration with respect to cellmate social interactions.

Exploring Duration of Cellmate Association Thresholds

Although the *ivprobit* routine assumes more plausible functional forms for the current treatment and outcome variables, the treatment effect it identifies might be misleading for at least two reasons. First, like each of the previous models, *ivprobit* assumes that each day of cellmate association impacts the releasee similarly, even though the only prior research on the relationships between socialization through associations in prison, time in prison, and time to release from prison suggests that this might not be the case (Wheeler, 1961; Garabedian, 1963; Wellford, 1967). Second, while *ivprobit*, like 2SLS, can handle unobserved heterogeneity it does not account for heterogeneity in treatment effects that might be associated with essential heterogeneity, in particular, selection on gains (Heckman et al., 2006).

Average prison peer effects estimated with *ivprobit* could be misleading if each day that a releasee spends with his cellmate does not impact the releasee in the same way (Merton, 1957; Wheeler, 1961; McGloin, 2009). Average prison peer effects may also be misleading if inmates remain in different durations of cellmate association for different reasons (e.g., own choice, correctional officer choices, and cellmate's choice). These different processes, the details of which are unobserved in the data, might yield different effects across the spectrum of releasees. Therefore, the ATE recovered via the *ivprobit* estimation strategy could be misleading in that it might over or understate the effect of number of days a particular releasee spends with a cellmate on rearrest (Heckman &

Vytlacil, 2005). To examine this possibility, duration of cellmate association thresholds were created.

The prison peer effects generated at each duration of cellmate association threshold are examined to see if they differ from those generated at the other thresholds. Duration of cellmate association thresholds are defined dichotomously, in terms of whether a releasee spends at least a particular number of days with his cellmate (e.g., at least thirty days, at least ninety days, etc.). The counterfactual is not spending at least that particular number of days with a cellmate (e.g., less than 30 days, less than 89 days, etc.).

In the current study, some cellmates spent only fifteen days with their longest-duration cellmate, whereas others spent more than 2,000 days in their most stable cellmate associations. The duration of cellmate association can, in principle, be dichotomized at each day across this wide range. Per the discussion in Chapter 4, thirty-day increments appear to be reasonable stretches of time in which to detect prison peer effects and changes in them over time (Wheeler, 1961; Garabedian, 1963; Wellford, 1967). The coefficients and p-values associated with these incremental duration threshold variables, estimated with 2SLS specifications for rearrest and any reoffending in both outcome models, are presented in Table 10. The shaded boxes indicate significance of the effect of duration on releasee reoffending.

*** [Table 10 here] ***

Per Table 10, few releasees spend less than less than two or more than twelve months of their stay with one cellmate. The sample size below the two-month and above the one-year thresholds is, therefore, likely to be inadequate to support analysis. That there are no relationships that are approach significance between duration of cellmate association and reoffending below the two-month threshold or above the one-year threshold supports this assessment.

There are no significant relationships between rearrest and the duration of cellmate association at any duration threshold. There are some thresholds for which the effect of duration on recidivism appears significant. These effects emerge primarily in the first outcome model that excludes RST scores.

In the first outcome model that excludes RST scores, effects are significant (or very nearly significant) for any recidivism from the 60-day threshold through the 240-day threshold, with the most significant effects ($p<=0.02$) occurring at the 120-day, 150-day, and 180-day thresholds. At each of the thresholds for which effects are significant, the direction of the effect is criminogenic. Moreover, the criminogenic effects generally appear to be increasing with the duration of cellmate association, as predicted by Clemmer (1940) and Sutherland (1947). As the releasees spend increasing amounts of time with their cellmates, their propensity to recidivate appears to increase.

In conjunction with the *ivprobit* results, this analysis suggests that there is no relationship between the duration of cellmate association and rearrest outcomes, but that there may be a relationship between the duration of cellmate association and recidivism outcomes. Additionally, there are some indications that bias may need to be overcome. The 2SLS estimates are certainly biased because the outcomes are dichotomous and also, potentially, due to the presence of essential heterogeneity in the relationship between duration of cellmate association and reoffending.

A Test for Essential Heterogeneity

Essential heterogeneity refers to response heterogeneity that proceeds from both selection on levels, or unobserved covariates, and selection on gains, or unobserved information about treatment outcomes (Heckman et al., 2006). Criminological assertions that inmates will enter into prison peer relationships in order to, for example, enhance their crime committing prowess (Bentham, 1830; Clemmer, 1950; Nagin, 2013), implicitly assume the presence of essential heterogeneity because they assume that inmates enter into prison peer relationships based on the potential gains to be had from them. To make this clearer, if observationally similar releasees' responses to their cellmates were homogeneous, they would respond to observationally similar cellmates in observationally similar environments in the same way. Under essential heterogeneity, observationally similar releasees' responses appear heterogeneous because researchers lack critical information about the determinants of the decision to remain with a cellmate, including whether the releasee expects to influence his own reoffending through that decision.

Detecting essential heterogeneity. Following Heckman et al. (2006) and Basu et al. (2007), it is possible to implement a straightforward process to test whether essential heterogeneity is present in the relationship between criminogenic cellmate associations and future criminal behavior. First, the choice model, which characterizes the decision to associate with a cellmate for a specific duration of time, is estimated. From that model, the probability that releasees select into particular durations of cellmate association is predicted. This probability is referred to as the propensity score. Different specifications of the outcome model, which relate rearrest and recidivism to the propensity to select into a particular duration of cellmate association threshold, are then explored. Specifically, the propensity score is interacted with the other covariates and/or higher order polynomial terms of the propensity score are introduced into the outcome models sequentially, as shown in [23]. If those terms are significant or if they are jointly significant, a nonlinear relationship between rearrest and the propensity to enter into a criminogenic cellmate association is indicated.

Reoffending = A + B(propensity score) + C(propensity score polynomial terms) +
D(releasee characteristics) + E(cellmate characteristics) +
F(pool characteristics) + G(other variables) +
H(propensity score interacted with D, E, F, G variables) + U [23]

Nonlinearities in the relationship between rearrest and the propensity to cell with a cellmate for a specific amount of time imply the presence of essential heterogeneity. To be clear, evidence of essential heterogeneity can manifest in multiple ways. If the higher-order polynomial terms are significant predictors of rearrest, essential heterogeneity is present. Similarly, if likelihood ratio tests show that the higher order polynomial terms improve the fit of the model, essential heterogeneity is present. Likewise, if likelihood ratio tests show that the interaction terms are jointly significant, essential heterogeneity is present. Each of these alternatives is a sufficient condition to establish the presence of essential heterogeneity. The steps used to detect essential heterogeneity in the current sample are detailed in 4.

*** [Figure 4 here] ***

The presence of essential heterogeneity indicates that instrumental variables techniques that attempt to recover average or local average treatment effects, such as 2SLS or Stata's *ivprobit* routine, cannot recover accurate treatment effects because treatment responses are not uniform for all members of the study sample. To recover meaningful information, the local instrumental variables technique can be employed to recover marginal treatment effects (MTE) at multiple decision points along the propensity score continuum.

*** [Table 11 here] ***

The presence of essential heterogeneity. Results from the tests for essential heterogeneity at each duration threshold from 60 days through 360 days are presented in Table 11. The presence of essential heterogeneity is consistently suggested for each model, except the second recidivism specification that includes risk scores, for which essential heterogeneity is indicated at some thresholds but not for others. The most consistent finding across the three models where essential heterogeneity is evidenced is that both the interaction and the propensity score squared terms are significant. Importantly, this is true for the first outcome model of recidivism where the duration effects appear significant. Neither the cubed nor the quartic propensity scores are significant above the squared propensity score. The local instrumental variables method can, therefore, be implemented without the highest order polynomial terms to estimate causal effects in the presence of essential heterogeneity.

There appears to be only scant evidence of essential heterogeneity in the second outcome model of recidivism. This finding is positive for an initial study of essential heterogeneity in prison peer effects. The results from the local instrumental variables implementation for this model should confirm the estimates generated from the simple IV specification: there should be no evidence of significant treatment effects on release reoffending for the second recidivism outcome. Due to the presence of essential heterogeneity in the other three models, a remote possibility remains that some releasees will experience significant treatment effects, even though the overall effect is null.

Summary of Preliminary Findings

In the current chapter, the preliminary work leading up to the full implementation of the local instrumental variables method to estimate prison peer effects was presented. A choice model and two outcome models were specified, estimated, and interpreted through multiple specifications, including linear probability models and instrumental variables specifications. Through the linear probability models, each of the two outcome models was explored for both rearrest and recidivism reoffending outcomes. The results (Table 7) suggested that the facility fixed effect variables, in addition to two of the originally proposed exclusion restrictions, were collectively related to the choice, but not to the outcome models. The instrumental variables were justified conceptually and statistical tests empirically supported their conceptual validity.

Stata's *ivprobit* routine was used to estimate the average effect of duration of cellmate association on releasee reoffending, as measured by the prevalence of rearrest and the prevalence of recidivism, which includes rearrest and reincarceration without rearrest. Only the first outcome model supported the hypothesis that the duration of cellmate association, on average, affects either reoffending outcome. (In three of four models, the coefficient on duration of association was insignificant.) Moreover, the social interaction variables, relative prior arrest and relative risk scores, were not significant predictors of either reoffending outcome. Cellmate prior incarceration predicted rearrest only in the first outcome model.

Per Chapters 2 and 4, duration thresholds were explored to see when during the course of a releasee's association with his cellmate prison peer effects might emerge and whether they might thereafter decay. At some duration thresholds, particularly in the first outcome model of recidivism, the effect of duration on recidivism was significant ($p<=0.05$) or very close to significant ($p<0.06$). Within the thresholds where treatment effects due to duration appeared significant, those treatment effects increased with the duration of association, until they simply became clearly insignificant.

Even though duration did not appear to independently and significantly impact rearrest, the variation within the duration thresholds suggested that essential heterogeneity might bias the results for both rearrest and recidivism. To detect the presence of essential heterogeneity, Heckman et al.'s (2006) simple test was employed at each duration threshold in each of the outcome models (Basu et al., 2007). For three of the four outcome specifications, the tests revealed the consistent presence of essential heterogeneity: the propensity score interaction terms were jointly significant, the propensity score squared terms were significant, and the inclusion of both improved the fit of the model.

Collectively, the analyses undertaken at each duration threshold suggested that if prison peer effects emerge, they are most likely to be discernible after 60 days and before

240 days with a cellmate, with the 150-day threshold looking most promising with respect to the strength and marginal significance of the detected effects. Theoretically, the six-month threshold is of particular interest, as the timing of average prisonization effects with the average onset and persistence of cellmate relationships coincides near that threshold, as was discussed in Chapters 2 through 5 (Wheeler, 1961; Garabedian, 1963).

The 150-day and 180-day thresholds, in addition to one other, the 120-day threshold, are the focus of the LIV analysis to be undertaken in Chapter 9. In that chapter, the choice of the 120-day threshold is defended in the context of an explanation of the common support of the propensity score, which precedes the final LIV analysis, through which prison peer effects are estimated.

CHAPTER 9: Local Instrumental Variables and Prison Peer Effects

In Chapter 8, the analytical model that underpins the local instrumental variables (LIV) implementation was developed. The choice model predicts the probability that releasee-cellmate associations meet duration thresholds. In a treatment effects (i.e., potential outcomes) framework (Roy, 1951; Rubin, 1978), treated releasees are those who are in cellmate associations that meet a particular duration threshold (i.e., the association lasts for a particular amount of time). Untreated releasees are those who are in cellmate associations that do not meet a particular duration threshold.

Two outcome models were specified. The first includes two criminal experience measures, prior incarceration and prior arrest; the second adds a criminality measure in the form of a risk score. These models estimate prison peer effects for two reoffending outcomes: rearrest, a traditional measure, and recidivism, which includes rearrest and reincarceration without arrest. Treatment effects are estimated with respect to duration and prison peer effects are estimated with respect to the criminality and criminal experience measures. To be clear, *treatment effects* are the effects on reoffending generated by duration and *prison peer effects* (i.e., social interaction effects) are the effects on the treatment effects generated by variation in the social interaction variables. In the current analytical framework, treatment effects must be estimated before prison peer effects can be estimated.

Introduction to Prison Peer Effect Estimation

Within duration thresholds, prison peer effects can be estimated through a similar process to the process that estimates treatment effects or they can be estimated by estimating treatment effects across the range of the values that the social interaction variables can assume. Treatment effects with respect to duration are identified using the local instrumental variables method (Heckman & Vytlacil, 1999, 2005). As the specification of choice and outcome models foretells, identifying treatment effects in the LIV framework is a multi-step process, beginning with estimation of the choice model.

The choice model and the support of the propensity score. The choice model predicts the probability that a releasee-cellmate association lasts a particular length of time. The probability, which is referred to as a *propensity score*, is a summary measure that reflects the propensity that a releasee will be treated based on the observed information contained in the administrative data provided by Pennsylvania State Police (PSP) and the Pennsylvania Department of Corrections (PADOC). Like all probabilities, propensity scores range from zero to one.

Propensity scores apply to individual releasees, but the distribution of propensity scores in the release cohort can also be characterized. An important property of the distribution of the propensity scores in the release cohort is whether it has *common support*. If a particular propensity score (e.g., a 50% probability of remaining with a cellmate for at least 150 days) has common support, it means that both treated (e.g., stayed with their cellmates for at least 150 days) and untreated (e.g., left their cellmates before 150 days) releasees have that propensity to remain with their cellmate. Common support indicates that the releasees who stayed with their cellmates can be compared with those who did not, given their propensity scores. *Full support of the propensity score* means that across the zero to one range of the propensity score distribution there are both treated and untreated releasees at each propensity score. In other words, full support indicates that, based on the observable information summarized in the propensity score, the treated and untreated groups are *balanced*, or observationally equivalent. As in experimental studies, which create balance on unobserved as well as observed characteristics, when treated and untreated groups are balanced, causal comparisons can more plausibly be made between them (Rosenbaum & Rubin, 1983, 1984; Heckman & Vytlacil, 1999, 2005; Apel & Sweeten, 2010b; Brave & Walstrum, 2014).[37]

For treatment effects to be estimated, the propensity score distribution must have common support. Marginal treatment effects (MTE) can be estimated wherever the propensity score has common support because there are treated and untreated releasees to compare at those points. Average treatment effects (ATE) can be estimated only when the propensity score has full support. If the propensity score does not have full support, estimation of ATEs must rely on (at minimum) the generally untenable assumption that partial sample characteristics generalize or extrapolate to the entire sample.

The current study asks whether prison peer effects can, on average, help to account for the average null prison effects observed in criminological literature (Nagin et al., 2009). As such, average treatment effects and how they are, on average, affected by prison peer interactions are the intended foci of the current analysis and its interpretations. It would, therefore, be advantageous for the support of the propensity score to be full at the duration thresholds considered.

[37] Naturally, there will not be treated and untreated releasees at each and every propensity score across the zero to one range of probability. Comparisons between treated and untreated releasees are made within narrow bins. In studies that rely on propensity score matching for identification, the support of the propensity score (i.e., whether treated and untreated groups are balanced) within narrow ranges can be assessed quantitatively using, for example, t-tests or by estimating standard bias (i.e., Cohen's d) within those bins (Apel & Sweeten, 2010b). The current study does not employ semi-parametric methods and, thus, does not rely on the support of the propensity score for identification (Heckman et al., 2006; Brave & Walstrum, 2014). Instead, parametric assumptions (i.e., normality) are made. However, the support of the propensity score indicates to which releasees the effect estimates apply.

The outcome model, marginal, and average treatment effects. The outcome model is a function of the propensity score predicted through the choice model. In addition to revealing the presence of essential heterogeneity, Heckman et al.'s (2006) test, which was performed in Chapter 8, indicated that the outcome models are a function of the propensity score, the propensity score squared, and the interaction of the propensity score with the covariates in the model. From estimates of those models, marginal treatment effects due to duration and marginal prison peer effects due to the criminal experience and criminality of cellmates are derived.

Marginal treatment effects are calculated by taking the derivative of the outcome with respect to the propensity score and, due to the presence of the interaction terms, the mean values of the covariates. This derivative is the local instrumental variable for which the LIV method is named (Heckman & Vytlacil, 1999, 2005; Heckman et al., 2006). In principle, the MTEs can be calculated for any values the covariates can assume, so variation in treatment effects can be estimated for particular segments of the sample, as designated by their observed characteristics. As the current analysis investigates how social interactions affect average treatment effects stemming from spending time with cellmates, it makes the most sense to allow the covariates to assume their average values. After the MTEs are estimated at the covariate means, average treatment effects with respect to the values of the covariates are calculated by integrating the MTEs over a propensity score distribution that has full support. In the context of the current study, these average treatment effects apply to particular durations of cellmate association at the mean covariate values. They are not the prison peer effects of primary interest.

Prison peer effect estimation. The process used to examine marginal treatment effects with respect to duration can be extended to derive marginal prison peer effects (MPPE) and average prison peer effects (APPE) with respect to the social interactions that occur during incarceration. Marginal and average prison peer effects are theorized to operate not through duration of cellmate association, but through the effect of cellmate criminal experience and cellmate criminality on releasee reoffending. Duration delineates temporal regions of cellmate association wherein prison peer effects might be detected and is also expected to moderate them, but the criminality and criminal experience of prison peers (i.e., cellmates) are expected to drive prison peer effects, as described in Chapters 2 and 4 (Sutherland, 1947; Matsueda, 1988; Warr, 2002; McGloin, 2009). The marginal and average prison peer effects operate within duration thresholds and through the social interaction variables: prior incarceration, prior arrest, and recidivism risk.

To estimate marginal prison peer effects, the derivative of the ATE can be taken with respect to each of the social interaction variables. Alternatively, average treatment effects can be estimated at different values of the social interaction variables. The latter approach, which relies on a new Stata routine: *margte* (Brave & Walstrum, 2014),[38] is the one taken in the current analysis. Changes in average treatment effects as a result of variation in the social interaction variables are the prison peer effects of primary interest to the current study. To clarify, the prison peer effects being estimated appear in the following equation [24]:

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[38] Select analyses were also completed via the author's own self-generated processes. The results are comparable. Presenting the results from the Stata routine provides the reader with an introduction to the output of an application available in a standard statistical software package.

$$APPE = \frac{\Delta E[Y_{1i} - Y_{0i} | X_{ij}]}{\Delta S_{ij}}$$

[24]

where Y_{1i} are outcomes when the duration threshold is met, Y_{0i} are outcomes when the duration threshold is not met, the X_{ij} are the covariates, and ΔS_{ij} are the changes in the social interaction variables. The social interaction variables, S_{ij}, are a subset of the X_{ij}. Thus, the average prison peer effect being estimated is conditional on the observed characteristics, which are reflected in the propensity score. Indifference, that is the MPPEs, are also conditional on observed characteristics, such that the indifference is with respect to the propensity not to meet a particular duration threshold given the observable characteristics, not between actually meeting that threshold or not.[39]

The rest of the chapter. This chapter proceeds in the following manner. The support of the propensity score at several duration thresholds is discussed. The choice of the 120-day, 150-day, and 180-day thresholds is defended. The process of estimating marginal and average treatment effects with respect to duration is described. Prison peer effects, both marginal and average, are then explored within the chosen duration thresholds. This chapter concludes with a brief summary of the findings.

Assessing Common Support of the Propensity Score

The local instrumental variables method is appropriate for estimating causal treatment effects under essential heterogeneity. Treatment effects are estimated with

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[39] To clarify further, indifference does not reflect indifference between, for example, spending 149 and 150 days with a time-intensive cellmate. Indifference is conditional on the observed probability of spending 150+ days with a cellmate or not. Therefore, individuals who exhibit the propensity to stay with best cellmate for 150+ days may have spent 151 or 2,000 days with their time-intensive cellmates.

respect to the releasees' propensity to be treated (i.e., their propensity scores). Propensity scores are generated through estimation of the choice model, which must include exclusion restrictions, as was described in Chapters 3, 4, and 8 (Heckman & Vytlacil, 1999, 2005; Brave & Walstrum, 2014).

In the current study, each releasee's propensity score is a summary measure of the contribution made by observed information (i.e., the data) to his probability of maintaining his cellmate relationship for a particular duration of time. Whether a releasee met or failed to meet a duration threshold primarily due to his own volition, his cellmate's volition, or the volition of the correctional officers is immaterial as long as the exclusion restrictions that support identification of the propensity score are robust, meaning they apply to more than a small subset of releasees. If the propensity score model lacks crucial information, particularly with respect to the exclusion restrictions, the propensity score estimates will be inefficient. The implication of that inefficiency is that common support can be indicated where there is none, which means that the identified treatment effects will be invalid for all or some of the sample under consideration (Heckman et al., 2006; Basu et al., 2007; Brave & Walstrum, 2014). Careful attention must, therefore, be paid to the choice of exclusion restrictions and to where along its range the propensity score distribution has common support. Chapter 8 gave due attention to the exclusion restrictions. The current section gives similar attention to the support of the propensity score at multiple duration thresholds.

*** [Figure 5 here] ***

The duration of cellmate associations, in combination with the timing of cellmate associations, is theorized to delineate when social interaction effects can be detected. In Chapter 8, the effect of duration of association on reoffending at the duration thresholds between 60 days and 240 days was shown to be significant, suggesting that it may take longer than a month for cellmate relationships to develop the capacity to exert social influence. That those effects increased with the duration of cellmate association before becoming insignificant after eight months further suggested that cellmate influence, while increasing over time, may eventually reach a saturation point. The timing of the pairings with respect to the releasees' release dates did not appear to impact reoffending in any of the models, even though prior research indicated that it should.

*** [Figure 6 here] ***

In terms of the potential to detect significant treatment effects and prison peer effects within duration thresholds, the significant effects point to the seven duration thresholds between the 60-day and 240-day thresholds. The common support of the propensity score will, therefore, be examined for those thresholds. Figures 5 through 11 depict the common support of the propensity score for the 60-day through the 240-day duration of cellmate association thresholds. Conglomerate graphs of the remaining thresholds are presented in the appendix associated with this chapter. In each of the graphs, the hollow bins represent releasees who do not meet the threshold while the shaded bins represent releasees who do meet the threshold.

*** [Figure 7 here] ***

The common support of the propensity score identifies the propensity score ranges within duration of cellmate association thresholds at which marginal treatment effects and the treatment effects derived from them can be identified. Common support is a characteristic of the distribution of propensity scores in the release cohort by whether or not a particular duration of cellmate association threshold is met (i.e., whether the releasees are treated or not). Within duration of cellmate association thresholds, propensity scores that have common support see realizations of releasees who both met threshold and those who did not. Where the propensity score has common support, the releasees who met the threshold are comparable to those who did not, given their observed characteristics. For example, if based on their observed characteristics two releasees each have a 40% chance of remaining with their cellmates for at least 180 days, but one stays with his cellmate (treated) while one does not (untreated), the propensity score for the 180-day threshold is said to have common support at 40%. The propensity score has full common support if, at each propensity score in the distribution from zero to one, there are releasees who received different treatments (e.g., met or did not meet the threshold).

*** [Figure 8 here] ***

The common support of the propensity score characterizes what is known about the sample. It also characterizes what is unknown. The propensity score is a prediction about treatment decisions based on what is known. But unobserved information also affects both treatment decisions and outcomes in observational studies. If unobserved factors played no role in treatment decisions, there would be no common support for the propensity score because all treatment decisions would be fully determined by the observed information summarized in those scores. Similarly, if there are no observed treatment decisions at particular propensity scores, there is a void of observable information about the determinants of the decisions at those scores. This typically happens at either very high or very low propensities to accept treatment. Without additional assumptions, estimated treatment effects cannot be generalized to individuals who might have those propensities, but do not appear in the available data (Heckman & Vytlacil, 1999, 2005; Heckman et al., 2006).

*** [Figure 9 here] ***

Figures 5 through 11 show that across the duration of association treatment thresholds for which marginal effects of duration on reoffending were found the support of the propensity score is either full or nearly full. While common support is narrow or not quite complete at the tails, particularly at the lower end of the propensity score distribution for the 60-day threshold and at the upper end of the 240-day distribution, the propensity score distributions at the 90-day, 120-day, 150-day, 180-day, and 210-day appear to have full support. As a result, marginal treatment effects, average treatment effects, and their corresponding prison peer effects can be estimated at each of those thresholds. They can also be compared across them.

*** [Figure 10 here] ***

Duration thresholds to be studied. Marginal and average treatment and prison peer effects are examined at three duration thresholds. Per the discussion in Chapter 8, the 150-day threshold was chosen because it is the threshold at which ATEs appeared strongest and most significant. Per the discussion in Chapter 2, the 180-day threshold was chosen because it comports with the thresholds explored in prior criminological research related to the timing of prisonization (Wheeler, 1961; Garabedian, 1963; Wellford, 1967). The third threshold balances the other two in timing (thirty days between each threshold) and, more importantly, in support over the propensity score.

At the 180-day threshold there are more releasees who do not meet the threshold than there are releasees who do. That is also the case at the 210-day and 240-day thresholds. In contrast, at the 120-day threshold there are more releasees who meet the threshold than there are releasees who do not. The choice of the 120-day threshold in addition to the 150-day and 180-day thresholds will, therefore, allow for comparisons among a threshold that favors the treated (120-day threshold), a threshold that supports a more even distribution of treated and untreated releasees (150-day threshold), and a threshold balanced in favor of the untreated (180-day). Each of the three chosen thresholds appears to have full support, meaning comparisons can be drawn across them with respect to each of the effects of interest in the current study: marginal and average treatment and marginal and average prison peer effects.

*** [Figure 11 here] ***

Estimating Marginal and Average Treatment Effects: An Explanation

Estimating marginal and average treatment effects with respect to duration is not the primary aim of the current study. However, the treatment effects with respect to duration are the primary effects identified via the LIV framework. Discussing identification of treatment effects, therefore, introduces the context in which the inquiry into prison peer effects will proceed: the baseline average treatment effect estimates are the estimates to which the average prison peer effect estimates are compared.

$$MTE(x,u_D) = E(\Delta|X = x, U_D = u_D)$$

To estimate marginal treatment effects, the derivative of the outcome (i.e., rearrest or recidivism) is taken with respect to the propensity score, as shown in [18], which is reproduced above. The resultant equation is then evaluated at small intervals where the propensity score has common support, for example 0.01 intervals along the zero to one continuum of the propensity score distribution. Interaction terms appear in the outcome model, which means that MTEs are calculated with respect to arbitrary values of the covariates. As this is mainly a study of whether average prison peer effects contribute to null or criminogenic average prison effects, the mean values of the covariates are applied.

$$ATE(X) = \int_0^1 \Delta^{MTE}(x,u_D)\,d\,u_D$$

When common support of the propensity score is full, an average treatment effect can be calculated by integrating the MTEs over the zero to one range of the propensity score, as shown in [19], which is reproduced above.[40] ATEs are calculated for each of the three duration thresholds under study because they each enjoy common support. While average treatment effects lack meaning when marginal treatment effects vary substantially, such as in the presence of essential heterogeneity, as summary measures they allow for a quick assessment of whether criminogenic prison peer effects, on average, outweigh crimino-suppressive prison peer effects, as predicted by the extant criminological literature summarized in Nagin et al. (2009).

The *margte* routine. Stata's *margte* routine is a local instrumental variables implementation created by Brave and Walstrum (2014). The *margte* routine has the capability to estimate average treatment effects in a local instrumental variables framework, via both parametric and semi-parametric methods. The routine produces standard regression output and a graphical depiction of the average and marginal treatment effects it estimates. The graphical outputs concisely represent the results of complex processes. As such, they are the primary outputs of interest and the primary outputs presented in the tables and figures associated with this chapter.[41]

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[40] To convert marginal treatment effects to other treatment effect parameters (e.g., local average treatment effects, policy relevant treatment effects, treatment on the treated, etc.) weights can be derived from the data (Heckman & Vytlacil, 2005, pp. 680-681). That derivation process is not undertaken in the current study, as it is not necessary for the study of marginal and average treatment effects.

[41] Per the local instrumental variables method, *margte* calculates marginal prison peer effects by taking the derivative of the reoffending outcomes with respect to the propensity score. The outcome model is a linear probability model. Although the reoffending outcomes are dichotomous, the convention in the literature is to estimate the marginal treatment effects for dichotomous outcomes using LPMs because LPMs are easier to implement and easier to interpret (Angrist & Pischke, 2009). In defense of this practice, Angrist and Pischke (2009, p. 107) write, "[W]hile a nonlinear model may fit the CEF [conditional expectation function] for LDV [limited dependent variables] more closely than a linear model, when it comes to marginal effects, this probably matters little." This is because the decision points at (or minute intervals over) which the MTEs are calculated are very small, so potential nonlinearities are unlikely manifest in such a small region. While exceptions wherein the estimates from LPMs may not substitute for estimates from nonlinear models have been artificially simulated (e.g., Dong & Lewbel, 2012), the similarity of the

Depiction of average and marginal treatment effects. Marginal and average treatment effects are depicted graphically with respect to "U_D," which is the propensity not to be treated. Per Chapter 7, the propensity not to be treated is the cumulative distribution of the unobservables (i.e., all the unobserved information grouped together), which is constrained to be uniform. The propensity not to be treated is a summary measure that indicates the contribution that the collective unobserved information makes to the decision to remain with a cellmate for at least, for example, 120 days, or not. The propensity not to be treated is inversely related to the propensity score (i.e., the propensity to be treated), such that if a releasee is treated (if $D_{it} = 1$), the value ascribed to the unobservables is greater than one minus the propensity score (Basu et al., 2007, p. 1139; Brave & Walstrum, 2014, p. 195). In each of the *margte* graphs, the solid line represents the MTEs, the dashed line, the ATE.

While it may seem convoluted to conceptualize treatment effects in this way, doing so enables the retrieval of otherwise unavailable information, as is illustrated by the graphs. The graphs depict the sum of the contributions made by unobserved factors to the treatment effect estimates. To put it another way, the graphs present information about how unknown factors (i.e., information that is not in the data) affect the estimates. The contribution of the known or observed factors is, of course, reflected in the regression estimates, which are presented for select analyses in the appendix to this chapter.

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directions and magnitudes of the coefficients between the LPM and probit specifications, which are not presented, but are available upon request, suggest that the current analysis is not an example of a real-world exception to Angrist and Pischke's (2009) generalization.

With respect to thinking about the contribution of the unobservables it is important, as was discussed in Chapter 7, to remember that U_D, the collective unobserved information, is not decomposable: the collective contribution of all of the unobservables, as a conglomerate, is reflected in U_D. It, therefore, includes all of the information unavailable to the researcher, but relevant to the releasees' decisions to remain with cellmates. Moreover, it includes elements of the agency of the correctional officers and cellmates who play roles in the persistence of prison peer relationships.

Guide to interpretation of the ATEs and MTEs. Figure 12 is a guide to interpreting the marginal treatment effect graphs produced by *margte*. The probability of not being treated increases along the X-axis. The treatment effect of remaining with a cellmate for several months, versus leaving him, on reoffending increases along the Y-axis. At low probability of not remaining with a cellmate for several months (i.e., meeting the threshold), releasees experience criminogenic effects. At high probability of not remaining with a cellmate for several months (i.e., not meeting the threshold), releasees experience crimino-suppressive effects. The average treatment effect (ATE) reported in the legend is the average of all of the marginal treatment effects estimated. More precise average treatment effect estimates are reported in Table 12.

*** [Figure 12 here] ***

Figure 13 depicts what the marginal treatment effect curves might look like when average treatment effects are criminogenic, null, and crimino-suppressive.[42] Again, the probability of not being treated increases along the X-axis, while the MTE estimates increase along the Y-axis. Assuming full support of the propensity score, MTEs can be estimated across the range of the propensity to not be treated. Whether ATEs are crimino-suppressive, null, or criminogenic depends on whether the bulk of the MTEs are crimino-suppressive, null, or criminogenic, as vertical shifts in the identical MTE curves illustrate. The first (highest) curve represents criminogenic average treatment effects, the second (middle) null average treatment effects, and the third (lowest) crimino-suppressive average treatment effects.

*** [Figure 13 here] ***

Average and marginal treatment effect estimates and interpretations. Figures 14 through 19 present the marginal and average treatment effect estimates from the first outcome model that excludes the risk score, as estimated with *margte*. Figures 20 through 25 present the marginal and average treatment effect estimates from the second outcome model that includes the risk score, as estimated with *margte*. Figures 14 through 16 and Figures 17 through 19 depict the average and marginal treatment effects of duration on rearrest at each of the thresholds under study. Figures 20 through 22 and Figures 23

[42] Note that the MTE curve does not have to assume this shape. It can, in fact, assume any shape. This shape, which is the shape of the MTE and MPPE curves in the current study, is adopted merely for consistency of exposition.

through 25 depict the average and marginal treatment effects of duration on recidivism at each threshold under study.

*** [Figures 14 through 19 here] ***

Each figure in Figures 14 through 25 consists of two graphs. The wavier graph on the left is estimated with maximum likelihood, under the assumption of normality, which is the default in the *margte* implementation. The regression output associated with each of these maximum likelihood estimates is presented in the appendix associated with this chapter.[43] The figure on the right is generated through the same specification, but forces a functional form that has a squared propensity score term, as indicated by the test for essential heterogeneity in Chapter 8. For each estimate, standard errors surrounding the marginal treatment effect estimates are generated via fifty bootstrapped replications of the estimation process.

*** [Figures 20 through 25 here] ***

In each figure, both the maximum likelihood (ML) and propensity score squared (PS2) specifications reflect a similar downward sloping marginal treatment effect curve

[43] Although the regression output from *margte* is presented in the appendix to this chapter, it is worth noting a few things about that output here. First, estimates for the treated and untreated groups are presented separately for the maximum likelihood regressions. This is by design in the *margte* routine, which is based on Stata's *etregress* routine. Second, the significant Mills ratios from those regressions indicate the presence of selection on unobservables and, thus, support the tests for essential heterogeneity from Chapter 6.

that is positive when the propensity to remain with a cellmate is high and negative when the propensity to be remain with a cellmate is low. Note that the addition of the squared propensity score term to each model changes the shape of the MTE curves, forcing them to follow straight lines, as opposed to waves. In addition, the imposition of the higher-order propensity score term, which is insignificant in the models, sometimes attenuates the ATEs, as shown in the figures and the regression output in the appendix to this chapter. For these reasons, only the maximum likelihood specifications will be presented when prison peer effects are examined. However, it should be noted that the standard error bands in the propensity score squared graphs are narrowest near the middle of the distribution of the propensity score (i.e., at a 50% probability not to be treated), which is where the subsample sizes are largest and where the estimated effect of duration on reoffending is nearest zero.

Across thresholds and specifications, the average treatment effect of duration on both reoffending outcomes is near zero and not significant. In each case, the marginal treatment effect curve crosses zero at about a 50% probability of being treated. Moreover, the MTEs are also generally insignificant, as is reflected by the shaded standard error bands surrounding each MTE curve. However, there does appear to be variation in the ATEs with respect to the unobserved and observed characteristics of the releasees and their environments. That is, the non-horizontal MTE curves, which include some significant point estimates, indicate the presence of essential heterogeneity.[44] Unobserved factors are affecting the estimates.

Even though the estimated marginal treatment effects are generally not significantly different than zero, considering what the downward-sloping shape of the MTE curve means is instructive in the context of this initial study of social interaction effects under essential heterogeneity. In these instances, when the contribution of the unobserved information is such that the probability of not staying with a cellmate for several months is high, effects are crimino-suppressive. When the unobserved factors indicate that the probability of not staying with a cellmate for several months is low, effects are criminogenic, as illustrated in Figure 12.

Characterizing the unobserved factors that are driving these effects is an exercise in hypotheticals. As discussed in Chapters 3 and 4, the unobserved factors that determine the length of time releasees spend with their cellmates are likely multitudinous and involve the agency of many people, including the releasees, their cellmates, other inmates, and correctional officers. Moreover, these many indeterminate unobserved factors, which may operate in concert or conflict with each other, cannot be logically separated from each other because they cannot be individually measured. However, their collective contribution to the observed response heterogeneity with respect to time spent with cellmates can be characterized.

[44] Selection on unobservables is also indicated by the significant Mills ratios reported in the regression output in the appendix to this chapter.

The ability to characterize the collective contribution of the unobservables (as well as the individual contributions of the observables) is a unique advantage of the LIV method. When unobserved factors encourage releasees to leave their cellmates before spending several months with them, those releasees' probability of reoffending is lesser; when unobserved factors encourage releasees to stay with their cellmates for several months or more, their probability of reoffending is greater. The collective unobserved factors that encourage longer cellmate relationships also encourage reoffending, whereas the collective unobserved factors that discourage longer cellmate relationships discourage reoffending. Whether these treatment effects are subject to prison peer effects is the subject of the following section.

Marginal and Average Prison Peer Effects Estimates

There are two approaches to estimation of prison peer effects. The first is similar to the estimation of treatment effects: to estimate marginal prison peer effects with respect to each of the social interaction variables in the model, the derivative of the average treatment effect at each threshold can be taken with respect to the social interaction variables. In the second, ATEs can be estimated with respect to the values that the social interaction variables can adopt. The latter approach is adopted in the current study, which relies on Stata's *margte* routine (Brave & Walstrum, 2014). The routine allows for specification of the values at which to compute the ATEs and MTEs. Variation in average treatment effects at varying values of the social interaction variables is equivalent to a prison peer effect.

How to determine whether cellmates exert prison peer effects. Average and marginal prison peer effects are the variation in the average and marginal treatment effects generated by the shifts in the social interaction variables. For each of the outcome models, baseline average treatment effect (ATE) estimates and average prison peer effect (APPE) estimates with respect to variation in the social interaction variables for both reoffending outcomes are presented in Table 12. The first section of Table 12 reports ATEs. The second, third, and fourth sections of the table report average prison peer effect estimates for each of the social interaction variables: cellmate prior incarceration, relative prior arrests, and relative risk scores. The APPEs are ATEs estimated at particular values of the social interaction variables within particular duration thresholds, as shown in the above equation [24]. Comparing the APPE estimates within particular duration thresholds ensures that time does not confound expectations about or interpretation of those estimates.

*** [Table 12 here] ***

Prior incarceration. Longest-duration cellmates who have a prior incarceration should increase releasees' probability of reoffending, relative to longest-duration cellmates without a prior incarceration, as predicted by differential association theory, which expects those with more criminal experience to exert more criminogenic effects (Sutherland, 1947). This means that, when looking at the results of the analyses that are presented in Table 12, the APPEs associated with cellmates who do not have a prior incarceration on record in Pennsylvania should be lower than the ATEs and the APPEs associated with cellmates who do have a prior incarceration should be higher than the ATEs.

Relative prior arrest. A positive relative prior arrest value indicates that a releasee has less criminal experience, as indicated by fewer arrests, than his longest-duration cellmate. A negative relative prior arrest value indicates that a releasee has more criminal experience, as indicated by more arrests, than his longest-duration cellmate. Per balance theory, APPEs on reoffending should be negative for releasees with negative relative prior arrest values and positive for releasees with positive relative prior arrest values (McGloin, 2009). Moreover, as relative prior arrest values increase, the effect on reoffending should, per differential association theory, also increase (Sutherland, 1947). Put another way, when positive, larger relative arrest differentials should yield larger increases in reoffending. When negative, larger relative arrest differentials should yield larger decreases in reoffending. There should be a positive relationship between the relative arrest measure and the APPE estimates reported in Table 12, whether reoffending is measured by rearrest or general recidivism.

Relative risk. The relative risk score measures operate similarly to the relative prior arrest measures. Negative relative risk scores indicate that the releasee has more criminality, whereas positive relative risk scores indicate that the longest-duration cellmate has more criminality. Negative relative risk scores should yield crimino-suppressive effects, whereas positive relative risk scores should yield criminogenic effects. The larger the differential in relative risk, the larger the effect should be, as the releasee and his cellmate attempt to achieve balance in their association (McGloin, 2009). From the negative end to the positive end of the continuum of relative risk scores, the average prison peer effects reported in Table 12 should be increasing, with large crimino-suppressive effects at the negative end giving way to large criminogenic effects at the positive end.

Prison peer effects as a function of prior incarceration. Figures 26 through 37 depict the average treatment effects on releasees' rearrest and recidivism at each treatment threshold for each outcome model, as moderated by the prior incarceration of their cellmates. In each figure, the graph on the left depicts marginal and average prison peer effects when the cellmates are first-time prison inmates (prior incarceration = 0), while the graph on the right depicts the marginal and average prison peer effects when the cellmates have a prior incarceration on record with PADOC (prior incarceration = 1).

*** [Figures 26 through 37 here] ***

Each of the graphs reveals no discernible differences in the reoffending outcomes of releasees who have more criminally experienced cellmates versus those who have less criminally experienced cellmates, as measured by the prior incarceration status of the cellmates. This is confirmed by the more nuanced average prison peer effect estimates reported in Table 12. While the insignificant prison peer effects of cellmate prior incarceration on releasee reoffending point consistently in the criminogenic direction and while the APPEs on recidivism are sporadically significant at lower duration thresholds, the only firm conclusion that can be drawn is that this analysis finds no support for the hypothesis that more criminally experienced cellmates, in terms of their incarceration histories, generate criminogenic peer effects in relation to less criminally experienced cellmates.

*** [Table 13 here] ***

Prison peer effects as a function of relative prior arrest. Figures 38 through 73 depict marginal and average prison peer effects, as attenuated by the relative difference in prior arrest of the releasees and their cellmates. In the data, relative prior arrest differentials range from –45 to +71. Marginal prison peer effects are presented for relative prior arrests between a -6 differential and a +6 differential, with positive numbers indicating greater cellmate criminal experience (i.e., more prior arrests) and negative numbers indicating lesser cellmate experience (i.e., fewer prior arrests) relative to the releasee. The range from -6 to +6 includes 75.87% (n=7,687) of the releasees, as shown in Table 13. Making comparisons within this range ensures that those comparisons are being made between several hundred releasees or more, as opposed to only several dozen releasees or fewer.

*** [Figures 38 through 73 here] ***

For brevity graphs of the MPPEs and APPEs are presented only for absolute differentials of two, four, and six. In each figure the graph on the left presents prison peer effects at the negative value of relative prior arrest (e.g., -6) while the graph on the right presents prison peer effects at the positive value (e.g., +6). Per Sutherland (1947) and McGloin (2009), wider differentials should evidence larger social interaction effects.

Contrary to the literature that expects social interaction effects, the graphs indicate that average treatment effects do not differ by relative prior arrest, thus indicating no evidence of discernible prison peer effects. This is true across the -8 to +10 continuum of relative prior arrest, as indicated in Table 12, which reports APPEs over the range of relative prior arrest values.[45]

*** [Table 14 here] ***

Prisons peer effects as a function of relative risk. Figures 74 through 97 depict marginal and average prison peer effects, as moderated by the relative risk scores of the releasees and their cellmates. Graphs are presented only for the second outcome model because the scores from PADOC's Risk Screening Tool (RST) were only included in the second outcome model, as described in Chapter 8. In the data, the relative risk scores

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[45] In general, the results from the prior arrest models are puzzling, even though they are not significant. Because these puzzles stem from insignificant effect estimates, they are discussed in a footnote, not the main text.

According to criminological theory, within duration thresholds (i.e., holding time constant) releasees with negative differentials should see their reoffending decrease, whereas releasees with positive differentials should see their reoffending increase. This is not observed for rearrest or for reincarceration. In each outcome model, at each duration threshold, the average treatment effect of duration on releasee recidivism is reduced as the prior arrest differential between the releasees and their cellmates increases.

This result contradicts differential association theory, which at the very least would expect increasingly wide positive differentials to exert increasingly criminogenic effects. Balance theory is also not supported from the perspective of the release: negative differentials should yield negative effects, positive differentials positive effects for the releasees, even though the cellmates' outcomes cannot be observed. This pattern is not seen at in either model, at any threshold, for either outcome.

To further complicate matters, for all but the first outcome model at the 150-day threshold, the ATE of duration on releasee rearrest is increased as the prior arrest differential between the releasees and their cellmates increases. While these effects on rearrest are expected in that increasingly wide positive differentials are predicted to exert increasingly criminogenic effects of rearrest, they also suggest that social interactions act in opposite ways on releasees who are reincarcerated without being arrested than on releasees who are simply rearrested, which is puzzling.

range from -7 to +7. The figures present marginal and average prison peer effects for rearrest and recidivism at each threshold for four absolute values of the relative RST score: four, three, two, and one. These values cover 98.03% (n=9,931) of the individuals, as indicated by Table 14. As was the case for relative prior arrest, the figures related to relative risk scores depict the negative differential score on the left (e.g., -4) and the positive differential score on the right (e.g., +4).

*** [Figures 74 through 97 here] ***

The figures indicate that there is no discernible difference in average prison peer effects by differences in relative risk between the releasees and their cellmates. Again, this finding provides no support for the criminological literature that expects social interactions to impact offending outcomes.

Overall outcomes. Table 12 presents average prison peer effect estimates over wider ranges of the social interaction variables. The null prison peer effect findings with respect to each of the criminal experience and criminality measures are confirmed by those estimates. Across the ranges of the criminality and criminal experience measures, there is very little evidence that cellmate criminality or criminal experience moderates the average treatment effects estimated for each duration threshold. There is no consistent evidence of average prison peer effects that indicates support for the hypothesis that prisons are learning environments in which criminals develop their criminality, or propensity to commit crime, as suggested by Clemmer (1940, 1950).

What the Current Study Finds

The current study finds no evidence of average prison peer effects on the rearrest or recidivism outcomes of the first-time PADOC release cohort. This null finding is not affected by the specification of the outcome model. Nor is it affected by the choice of social interaction variables, which are indicators of inmates' criminality and criminal experience. The null APPE estimates are consistent across the three duration of cellmate association thresholds.

While arguments that prisons, on average, are schools of crime, find no support in the current study, the notion that prison peers can be beneficial to some first-time prison releasees (i.e., reduce their reoffending), while harming others (i.e., increasing their reoffending) does find support. Substantial and consistent essential heterogeneity was found in the in the relationship between reoffending and cellmate social interactions. This heterogeneity remained despite the presence of numerous theoretically relevant controls.

The presence of essential heterogeneity was established by the tests presented in the previous chapter and the significant Mills ratios reported in the *margte* output, examples of which appear in the appendix to the current chapter. In addition, essential heterogeneity is evident in the graphical output. At each threshold, the shape of the MTE curve is downward sloping. Were no essential heterogeneity present, the MTE curves would be flat (i.e., horizontal). The marginal prison peer effect curves mirror the MTE curves. The estimated MPPEs in each of the graphs (Figures 26 through 97) range from about –0.2 to +0.2. Each MPPE curve follows a symmetrical downward-sloping pattern, crossing zero at about a 50% probability of meeting the duration threshold in question. Moreover, the propensity score squared MTE graphs in Figures 14 through 25 indicate that the standard errors are narrowest near this mid-point. It is, therefore, not surprising that the average prison peer effect (and average treatment effect) parameter estimates are precisely estimated in this region. Where the marginal prison peer effects are criminogenic or crimino-suppressive (i.e., at the tails), they are generally larger, but also more imprecisely estimated. Moreover, when the MPPEs at the tails are significant, they typically balance each other, thus reinforcing the central tendency toward null APPEs.

The marginal prison peer effect estimates are significant only in rare instances and only over a very small range of the propensity to not be treated, at most a 20% probability of not remaining with a cellmate for a particular number of days. Only at very high and very low probabilities of meeting the duration threshold are MPPEs sometimes significant. At high probabilities of remaining with a cellmate for a particular number of days (or low probability of not remaining with a cellmate for a particular number of days), if the MPPEs are significant, they are always criminogenic. At low probabilities of remaining with a cellmate for a particular number of days (or high probability of not remaining with a cellmate for a particular number of days) if the MPPEs are significant, they are always crimino-suppressive.

Crimino-suppressive effects countervail criminogenic effects. Put another way: when factors that are not included in the data encourage releasees to stay with their cellmates, the releasees experience criminogenic effects that are rather large (e.g., a 20% increase in the probability of being rearrested), whereas when factors not included in the data encourage releasees to leave their cellmates, the releasees experience crimino-suppressive effects that are similarly large (e.g., a 20% decrease in the probability of being rearrested). However, in general, those effects are not significantly different from zero.

Keeping in mind that characterizing the unobservables is an hypothetical exercise, the criminological framework outlines in Chapter 2 can provide a plausible explanation of these observations. For example, unobserved criminal attitudes and behaviors on the part of the releasees and their cellmates can explain the observed outcomes.

Releasees high in criminality might have a strong desire to stay with highly skilled criminal cellmates (e.g., Shaw, 1966) because those releasees believe they can learn techniques relevant to particular criminal behavior from those cellmates, as suggested by Bentham (1830), Clemmer (1950), and Nagin et al. (2009). The criminality and desires of the releasees are unobserved, as are the particular skills that those releasees may hope to learn from their cellmates. Nevertheless, the contribution those unobservables make to the detected effects is both observable and criminogenic.

Conversely, releasees who are low in criminality might find the excessive criminal attitudes of their cellmates distasteful. This could and, according to the PADOC correctional officers, often does happen in the case of inmates assigned to cellmates who are sex offenders (personal communication, 2013). Releasees assigned to cellmates whose criminality they find unacceptable my want to desist from their cellmate associations. They may also want to desist from crime in order to avoid a prison environment where they might be compelled to interact with distasteful individuals. In this example, the criminal attitudes and behaviors releasee and his longest-duration cellmate are equally unobservable. What is observable, however, is their collective crimino-suppressive prison peer effect.

In Summary

The current study finds very little support for the hypothesis that social interactions between cellmates can account for the average criminogenic effects of prison on reoffending outcomes. The longest-duration cellmate associations maintained by the members of a release cohort from the Pennsylvania Department of Corrections were examined to see if the prior criminal experience and criminality of the cellmates would influence the reoffending outcomes of the releasees who spent varying amounts of time with their longest-duration cellmates. On average, no consistent significant associations were found between duration of cellmate association and the releasees' reoffending outcomes, which included rearrest and recidivism, defined as rearrest and reincarceration without rearrest. Estimating average prison peer effects across the range of the cellmate criminality and criminal experience measures also revealed no significant variation in those effects. In other words, no evidence of average prison peer effects was found. However, considerable evidence of marginal prison peer effects was found: substantial essential heterogeneity remained despite the inclusion of numerous statistical controls.

While the contribution that the unobserved determinants of decisions cannot be decomposed into its constituent elements, that the prison peer effect estimates evinced heterogeneity despite dozens of control variables suggests the need for improvement on two fronts. First, more data, particularly regarding criminal attitudes and definitions, can be collected from incoming inmates. Second, the local instrumental variables method can be refined to account for multiple decision makers in a social interactions framework.

CHAPTER 10: Discussion

The consensus in the criminological literature is that the average effect of incarceration on reoffending is null or criminogenic, rather than crimino-suppressive. Nagin et al. (2009) interpret this prison effect as a failure of specific deterrence because, in their view of the extant literature, prison should deter those who experience it from future offending. In other words, the effect of prison should be crimino-suppressive, not criminogenic. The current study has sought to establish whether average prison peer effects can be held accountable for some portion of the failure of incarceration to reduce reoffending. The evidence presented in the preceding chapters suggests that they cannot.

That is not, however, the end of the story.

Although average prison peer effects are null, they are not homogenous. Considerable response heterogeneity, which is attributable to essential heterogeneity (Heckman et al., 2006), remained evident in the marginal prison peer effect estimates, despite the inclusion of numerous theoretically relevant controls in both the choice and outcome models. That considerable response heterogeneity remained despite the inclusion of controls thought be relevant to the production of reoffending suggests the potential for considerable bias in previous estimates of social interaction effects, which included fewer such controls and/or used methods unable to handle essential heterogeneity, such as multiple regression and instrumental variables techniques.

Naturally, the preceding conclusion is not without its caveats. The inability to construct true attitudinal measures of criminality, as required by criminological theory, and the application of a single-decision maker method to a multiple decision-maker problem are major, but not the only, shortcomings of the current study and, indeed, many criminological studies. Moreover, each of these shortcomings may have impacted the results. Fortunately, both shortcomings have the potential to be addressed in future work.

A Succinct Summary of the Current Study

According to criminological theory, peer or social influence arises during social interaction. Through ordinary learning mechanisms, what Sutherland (1947) called definitions (i.e., attitudes, motivations, and rationalizations, per Matsueda (1988)) and behaviors, both antisocial and prosocial, are discussed, modeled, encouraged, and discouraged (Skinner, 1952; Sutherland & Cressey, 1955; Bandura, 1962; Burgess & Akers, 1966; Matsueda, 1988; Akers, 2009; Kahneman, 2011). Evidence of social influence (i.e., a peer effect) emerges as increased or decreased criminal behavior and criminal definitions. Whether peer effects excite or abate criminal behavior and attitudes depends on the relative criminal experience and criminality of the interacting individuals (Sutherland, 1947, McGloin, 2009).

Socialization to the prison environment through social interaction, which has been termed prisonization, is the process of criminal peer influence applied to the context of incarceration (Clemmer, 1940, 1950). Prisonization, which occurs primarily in interaction with other inmates, has been shown to vary with the duration of time inmates have served as well as with the duration of time they have left to serve, such that prisonization increases through mid-sentence then decreases as inmates approach their release dates (Wheeler, 1961; Garabedian, 1963; Wellford, 1967). Moreover, although prisonization effects may decelerate after peaking during the course of a prison stay, they do appear to remain elevated over pre-prison levels and to persist for some time after inmates are released from prison. While not all inmates exhibit the same pattern of prisonization

(Garabedian, 1963), on average, first-time prison inmates appear less prisonized at baseline than do returning inmates (Wheeler, 1961).

Developmental cascade theory may account for the persistence of prisonization due to prison peer effects (Masten et al., 2005; Dishion et al., 2010). An hypothetical cascading prison peer effect process might involve cellmate interactions that lead to deviancy or criminality talk, through which criminality increases such that it engenders future criminal behavior, because increased criminality due to prison peer interactions influences all subsequent interactions that the inmate has post-prison (Sutherland, 1947; Lorenz, 1972; Dodge & Dishion, 2005; Sherman & Harris, 2013).

To examine potential prison peer effects, the current study focused on first-time releasees, longest-duration cellmates, and several social interaction variables that reflect the criminal experience and criminality of the releasees and their cellmates. A cohort (n=10,131) of first-time releasees was chosen because first-time inmates are theorized to be likeliest to experience the strongest prison peer effects (Wheeler, 1961; Nieuwbeerta et al., 2009). The cellmates who celled with each first-time releasee for the most days were identified because they were expected, based on their time-intense associations with the releasees, to exert the strongest prison peer effects relative to other cellmates who engaged in less time-intense associations with the members of the first-time release cohort (Sutherland, 1947; Agnew, 1991; Warr, 1993).

Social interaction variables that delineate cellmates and releasees based on their criminal experience and criminality were then identified. Cellmates with prior incarceration records were expected to exert more criminogenic prison peer effects relative to first-timers because they have more extensive criminal experience, as indicated by their incarceration histories. Similar reasoning led to the expectation that cellmates with lengthier arrest records would be likelier to exert criminogenic effects than those with shorter arrest records. Cellmates with higher risk scores, which reflect criminality, were likewise expected to exert more criminogenic prison peer effects relative to those with lower risk scores. Level cellmate measures were considered relative to level releasee measures to more fully account for variation in peer influence (McGloin, 2009). The relative distance between the criminal experience and criminality of a releasee and his longest-duration cellmate was expected to matter. More criminal releasees were expected to experience crimino-suppressive prison peer effects as a result of interacting with relatively more prosocial cellmates. Releasees paired with relatively more antisocial cellmates were expected to experience criminogenic prison peer effects.

The current study attempted to isolate statistically significant average prison peer effects on reoffending using the local instrument variables (LIV) method (Heckman & Vytlacil, 1999, 2005). The LIV method is a choice-theoretic method that isolates the effect of binary decisions through a two-stage process. In the first stage, the probability of making a dichotomous decision is predicted. In the second, that probability (i.e., propensity score) is used to predict the outcomes of interest.

The dichotomous first-stage model predicts the probability that two inmates cell together for a particular duration of time. Duration was chosen to characterize cellmate associations because prior criminological research had shown that prison socialization processes depend on it nonlinearly, such that prisonization accelerates, peaks, and then declines through prison stays (Wheeler, 1961; Garabedian, 1963; Wellford, 1967). The second-stage predicted two outcomes of prison peer interactions: the prevalence of rearrest and the prevalence of more general recidivism, defined as rearrest or reincarceration without arrest. Within the limitations of the data (i.e., self-report data were not available), these outcomes capture reoffending such that it reflects the least intense intervention by the criminal justice system (Maltz, 1984; Thornberry & Krohn, 2000).

To causally identify prison peer effects using any method that relies on instrumental variables, including LIV, at least one exclusion restriction that directly predicts the celling longevity decision, but only indirectly predicts reoffending must exist, both conceptually and in the available data (Imbens & Angrist, 1994; Heckman & Vytlacil, 1999, 2005; Bushway & Apel, 2010). Multiple exclusion restrictions were theoretically and empirically justified, such that they were demonstrated to be plausible, strong and sample-wide predictors capable of isolating average prison peer effects on reoffending outcomes (Basu et al., 2007).

Through the LIV framework, the longest-duration (i.e., most stable or most time-intense) cellmate associations maintained by the members of a first-time release cohort from the Pennsylvania Department of Corrections (PADOC) were examined to see if the prevalence of releasee reoffending, as reflected in rearrest and a more general recidivism measure, was affected by the prior criminal experience and criminality of those cellmates. It was not. Multiple decision thresholds at 30-day increments of the duration of cellmate association were investigated to see if average prison peer effects varied as the duration cellmate association was raised from 120 to 150 to 180 days. They did not. The null findings pertaining to average prison peer effects held across duration thresholds, for multiple model specifications, and both reoffending outcomes. That average peer effects were found to be consistently null with respect to each of the social interaction variables and at each of the duration thresholds obviates the need to discuss the questions enumerated in Chapter 4. Average prison peer effects of longest-duration cellmates on releasees are null at multiple duration thresholds, for multiple behavioral outcomes and social interaction variables, and regardless of model specification.

Importantly, although the APPEs were estimated to be null, marginal prison peer effects were shown both to vary and to be significant for some releasees. That is, essential heterogeneity (Heckman et al., 2006) was shown to be present in the relationship between releasee reoffending and prison peer interactions. The biases due to unobserved heterogeneity are evident in comparisons between the effect estimates from linear probability models (LPM), instrumental variables (IV) specifications, and the local instrumental variables models. Initially significant and crimino-suppressive average prison peer effect estimates from LPMs became insignificant in three of the four models and appeared to point in the criminogenic direction under the IV specifications, including the *ivprobit* specification, which employs the correct functional form with respect to the nature of the instrumental and outcome variables.

The presence of essential heterogeneity was confirmed at each of the thresholds between 30 and 360 days in both outcome models using Heckman et al.'s (2006) test. It was also evident in the final LIV estimates at the 120-day, 150-day, and 180-day thresholds, which reported significant Mills ratios and evinced downward-sloping marginal prison peer effect (MPPE) curves. Although the APPEs were near-universally insignificant for both reoffending outcomes across the duration thresholds and outcome models, the LIV models also established that MPPEs were often significant, particularly at extreme values of the propensity not to maintain a cellmate association for several months, that is, when the probability that a releasee would remain with or leave his was very certain. Moreover, some MPPEs operated in the criminogenic direction, while others operated in the crimino-suppressive direction.

The presence of essential heterogeneity and variation in the estimated marginal prison peer effects indicates that average prison peer effects do not accurately characterize the effect of cellmates on releasees in most circumstances. Some releasees are unaffected by their prison peers, but other releasees are more likely to be arrested or reincarcerated without an arrest after spending time with their cellmates, while still others are less likely to be arrested or reincarcerated without an arrest after spending time with their cellmates.

The releasees who experience criminogenic effects are those who, for unobserved reasons, stay in their longest-duration associations for at least several months. The releasees who experience crimino-suppressive effects are those who, for unobserved reasons, leave those associations before several months have elapsed. This was true in both model specifications for both rearrest and more general recidivism outcomes and at each of the three duration thresholds (120-day, 150-day, and 180-day) examined.

While speculative, a primary unobserved factor driving these outcomes could be unmeasured criminality. Releasees with more criminal propensity may want to cultivate more intense criminal associations that enable them to reoffend (e.g., Bentham, 1830; Clemmer, 1940; Lerman, 2009), while releasees with lesser criminal propensity may want to dissociate themselves from such associations in order to curb their reoffending (e.g., Wheeler, 1961; Giordano et al., 2002; Crewe, 2007).

That prison peer effects were estimated to be null, on average, was an unexpected finding given both prior theory and prior research. The first-time PADOC releasees were paired with time-intensive cellmates who, on average, had more extensive arrest histories, more prior spells of incarceration, and higher risk scores. In this scenario, criminological theory predicts that prison peers will, on average, exert criminogenic effects (Clemmer, 1940; Sutherland, 1947; McGloin, 2009) and that those effects have the potential to cascade over time and through domains (Masten et al., 2005; Dishion et al., 2014). Research has also indicated that this is likely to be the case (e.g., Wheeler, 1961; Bayer et al., 2009). Methodological, operational, and theoretical limitations may each have contributed to the null APPE findings. The main foci of this final chapter are to explore why those APPE findings may appear null and to argue that future prison peer effect studies should focus on marginal, rather than average, effects.

Methodological Limitations

Methodologically, prison peer effects were explored within the context of their capacity to moderate the average treatment effects demarcated by the duration of cellmate association. After essential heterogeneity (Heckman et al., 2006) was detected in the relationship between time spent with cellmates and reoffending, a local instrumental variables framework (Heckman & Vytlacil, 1999, 2005) was developed to estimate prison peer effects. The LIV framework is the most appropriate framework to adopt when essential heterogeneity is present and causal effect identification is desired (Heckman et al., 2006; Brave & Walstrum, 2014).

In most criminological explanations of offending, the presence of essential heterogeneity is implicit: unobserved criminality is a factor both in decisions that affect criminal behavior and in the criminal behavior itself. This is true of Clemmer's (1940) differential association-based (Sutherland, 1947; Wellford, 1967) theory of prisonization, wherein inmates must decide how deeply to assimilate into the prison environment. How complete their prisonization becomes then impacts their post-prison offending patterns.

According to Clemmer (1950), the process of prisonization affects and is affected by inmates' criminality, which also influences their future (i.e., post-prison) criminal behavior. Essential heterogeneity is, therefore, implicit in his hypothesis that prisons are learning environments. Essential heterogeneity is also expected in the current prison peer effect framework, which relies primarily on the work of Sutherland (1947), Clemmer (1940, 1950), Wheeler (1961), Masten et al. (2005), and McGloin (2009). Inmates are expected to remain in cellmate relationships due to unobservable factors (e.g., their criminality; the criminality of their cellmates; the disposition of the correctional officers), which are expected to impact reoffending independently as well as through the duration of cellmate association. Prison peer effects are expected to persist over time as causally shifted criminality influences subsequent interactions and behaviors in the post-prison environment (Masten et al., 2005; Dishion et al., 2010; Dishion, 2014).

Although the LIV framework allows for causal identification of treatment effects under essential heterogeneity, it has at least three weaknesses when applied to identification of prison peer effects. First, in the context of prison peers, the treatment decision is less well-defined than it is in other contexts. In educational contexts, for example, the decisions to graduate high school or to finish college are well-structured binary choices (e.g., Heckman et al., 2006; Heckman & Urzua, 2010). Celling decisions are naturally binary in that inmates are either placed together in a cell or not. However, in an analytical framework in which cellmate pairs are already determined, how to characterize the nature of those pairings to preserve the binary nature of the pairing decision is not obvious.

In the current operationalization, the decision was made to characterize cellmate associations based on their duration. That decision may have been consequential to the null outcomes. Other cellmate association characterizations, which may be both more relevant to the study of prison peer effects and less likely to evince null effects, are also possible, as outlined in the operational weaknesses section below.

The second weakness of the LIV method as it was applied is that it requires a large sample if interaction effects for continuous variables are to be explored. Ultimately, the sample size may not have been large enough to support identification of causal effects at the extremes of the propensity score distributions, which is where significant effects appear to be emerging and also where the tails have the fewest observations.

Finally, in applying the LIV method to the problem of identification of social interaction effects, the agency of the releasee was adopted as the primary driver of the treatment, which was defined as the persistence of the prison peer relationship. While adopting this perspective avoids the SUTVA problem, it fails to accurately characterize the social relationship as involving the agency of the releasee's cellmate and the agency of the correctional officers, as well as the agency of the releasee.

Cellmate association characterizations. In the current prison peer LIV framework, the criminality of the releasees and their cellmates are theorized to predict both the duration of cellmate association and releasee reoffending. The choice to treat duration as the determining factor in the production of prison peer effects on reoffending was appropriate in the prison context for at least three reasons. First, duration is inextricably linked to prison effects because prisoners are sentenced to spend particular amounts of time in prison. Second, when prisoners are assigned to cellmates their association may need time to develop to the point where prison peer effects become detectable. Finally, prior research had shown duration to be a factor in the degree to which inmates become prisonized (Wheeler, 1961; Garabedian, 1963; Wellford, 1967).

Monthly duration thresholds between one month and two years of cellmate association were explored to see when during the course of a cellmate association prison peer effects might be detectable. Three thresholds were explored: the 180-day threshold comported with prior criminological work on the timing of prisonization relative to prison stays and the timing of a pairing with a longest-duration cellmate, as discussed in Chapter 2. The 150-day threshold seemed most promising in terms of the potential to detect prison peer effects because that is where the effects appeared most significant, as shown in Chapter 6. The 120-day threshold balanced the other two in terms of the distribution of releasees over the propensity score, as shown in Chapter 9. Average prison peer effects were insignificant at all three thresholds.

Although duration is a reasonable potential delineator of the development of prison peer relationships, it may not be the lens through which prison peer effects should be investigated. In particular, duration is generally theorized to moderate prison peer effects, not to generate them independently (Sutherland, 1947; Glaser & Stratton, 1961). Other aspects of human relationships that do not involve time may, therefore, better serve to delineate treatment choices in the LIV framework.

Obvious candidates to substitute for duration as delineating characteristics of releasee-cellmate associations are the homophily variables, which reflect similarity between releasees and cellmates on particular characteristics. Homophily is evident in all human relationships (Becker, 1974; Cohen, 1977; Kandel, 1978; Buss, 1985; Mare, 1991; McPherson et al., 2001; Weerman & Smeenk, 2005), but how it affects the outcomes of those relationships is unclear (e.g., Glueck & Glueck, 1950; Gottfredson & Hirschi, 1990; Hartup, 2005; Mouw, 2006). In the current framework, the homophily variables were strongly predictive of the duration of cellmate association, but did not collectively appear to significantly influence recidivism outcomes, although they did influence rearrest outcomes. However, the homophily variables created for this study generally reflected demographic similarities, rather than similarities based on criminality or criminal experience.

Through the arrest history data provided by the Pennsylvania State Police, it may be possible to construct measures of criminal proclivities and skills, as evidenced by the types of prior crimes that prisoners committed. Similarity or difference with respect to criminal experience measures might provide a better means through which to predict the formation of cellmate associations and the reoffending outcomes theorized to proceed from them. They may also serve as a better test of the "schools of crime" hypothesis, which expects inmates to develop greater criminality that foments reoffending (Bentham, 1830). For example, it may be possible to determine whether inmates specialized in particular crime types before prison and whether those specializations changed after prison, as a result of social interactions (e.g., Bayer et al., 2009).

Sample size. An additional limitation of the LIV method as applied was the sample size. While a first-time release cohort consisting of 10,131 releasees seemed like an adequately large sample, it was not. That the sample size emerged as a limitation was a direct consequence of the implementation of the method, which requires balanced comparison groups (Heckman & Vytlacil, 1999, 2005; Apel & Sweeten, 2010b).

The choice model in the current LIV framework predicts the probability that releasees stay with their cellmates for particular lengths of time. That propensity score is then used to predict prison peer effects on reoffending outcomes. The support of the propensity score distribution in the sample, in part, determines to whom the predicted prison peer effects can be generalized. When the support of the propensity score is full, treatment effects have the potential to be generalized to the entire sample.

Full support of the propensity score means that across the zero to one range of the distribution of propensity scores, there are individuals who share similar propensity scores but were treated differently: some remained with their cellmates for several months (i.e., were treated) while others did not (i.e., were untreated). In other words: the treatment and control groups must balance on the propensity to be treated, not the treatment (i.e., specific duration) itself. Where the treatment and control groups balance, marginal prison peer effects (MPPE) can be estimated. If the propensity score has full support an average prison peer effect (APPE) can be calculated by integrating the estimated MPPEs over the range of the propensity score.

Determining releasees' propensity scores as a function of treatment (i.e., meeting a duration threshold or not) both divides the cohort into treatment groups and distributes it along the range of potential propensity scores. While this process creates appropriate comparison groups as a function of the propensity score within the treatment and control groups (i.e., people with the same propensity to be treated who were both treated and not treated), it can also create very small propensity-score dependent comparison groups, particularly at the extremes of the propensity score. In the current analysis, these divisions were then exacerbated because marginal prison peer effects were estimated at different levels of the social interaction variables, thus further subdividing the sample.

To make this more concrete, imagine that the 10,000 releasees are distributed uniformly in equal-size treated and untreated groups across the range of the propensity score. The addition of the prior incarceration social interaction indicator creates four, again equally-sized groups: treated-prior incarceration, untreated-prior incarceration, treated-no prior incarceration, and untreated-no prior incarceration. Were the marginal prison peer effects estimated in 100 bins along such a distribution, the approximately 2,500 releasees in each of the four categories would be dispersed in groups of twenty-five on either side across the propensity score continuum, thus creating very small comparison groups.

With respect to the relative risk and relative prior arrest measures, the comparison groups through which the marginal prison peer effects are estimated have the potential to become even smaller. This can be seen by examining crosstabs of the social interaction variables at deciles of the propensity score, which are presented for select deciles at the 150-day threshold in the appendix associated with this chapter. It is clear from these crosstabs that the wide standard error bands around the estimates (e.g., Figures 14 through 25), particularly at extreme values of the propensity score, are driven by small sample size. To improve the current analysis, it may be possible to select a larger sample of first-time PADOC releasees that covers more release years. Alternatively, the sample could be expanded to include those releasees with prior incarcerations. Still another possibility is to reframe the analysis such that these interactions are not a part of it. The latter might be accomplished by creating differentiating characteristics of the releasee-cellmate associations based on the social interaction variables.

In addition to suggesting a means through which this study can be improved, this discussion of the support of the propensity score and its implications suggests an empirical explanation for the heavily context-dependent effects estimated in the social interaction literature (Hartup, 2005; Mouw, 2006; Gangl, 2010; Horney et al., 2012; Sacerdote, 2014) and for the null effects estimated via robust IV designs (Angrist, 2013). Samples in which there is not balance with respect to the propensity score may generate biased effect estimates because apples are being compared to oranges, as described in Chapter 3. This is likelier in smaller samples, as the cross-tabulations in appendix illustrates, because there are far fewer individuals to balance. The implication, then, is that samples could be highly skewed toward one end of the propensity score distribution (e.g., the end in which criminogenic effects are generated or the end in which crimino-suppressive effects are generated) and/or large portions of the sample might lack appropriate comparisons. In either case, average treatment effects estimated without appropriate weighting will be biased due to these imbalances (Heckman & Vytlacil, 2005). Similarly, instrumental variables implementations, such as those recommended by Fletcher (2009, 2012), often fail to generalize to the entire sample (i.e., they are localized), even though that is the goal. That is, LATEs are estimated, when ATEs are desired (Heckman et al., 2006; Bushway & Apel, 2010).

Single decision makers. The current application of the LIV method is further limited because the LIV framework is a potential outcomes framework based on the Roy (1951) model, which means the LIV framework is a single decision-maker framework, not a multiple decision-maker framework. Although, as was discussed in Chapter 7, potential stable unit treatment value assumption (SUTVA) violations can be avoided by adopting the perspective of a single decision maker, applying the model in this way is unlikely to accurately model the decisions that result in particular cellmate association durations because multiple decision makers can influence those decisions. While all regression-based models (i.e., all analyses based on the linear-in-means model) of peer influence make the same assumption (Wellford, 1973; Manski, 1993; Brock & Durlauf, 2001, 2007; Mouw, 2006; Gangl, 2010; Graham, 2011; Sacerdote, 2014), making that assumption does have implications for the interpretations that can be made from this LIV analysis.

The main implication of the decision to adopt the perspective that the releasee (i.e., the unit of analysis) is the decision maker is that the collective unobservables that contribute to essential heterogeneity in the relationship between cellmate associations and reoffending outcomes reflect some combination of unobserved determinants of releasee decisions (e.g., criminal attitudes and beliefs), unobserved aspects of cellmate and correctional officer decisions (e.g., dispositions, correctional programming needs), and any other unobserved factors (e.g., characteristics of other potential cellmates; unit cultures, etc.) that might influence reoffending outcomes. While their collective contribution can be characterized, the collective unobserved determinants of decisions cannot be separated from each other.

Were the LIV model extended to accommodate multiple decision makers, it might be possible to separate the unobservables into unobservables attributable to each decision maker. Doing this would highlight areas where future research could concentrate (e.g., on the releasee and his cellmate, on the correctional system, or on some other area of inquiry) to better understand individual reoffending outcomes. This extension to the LIV model is planned for future work.

Operational Limitations

Operationally, the choices made regarding the specific releasees, cellmate relationships, social interaction variables, and reoffending outcomes to evaluate may have limited the potential for prison peer effects to be captured and generalized. First-time releasees were chosen because they were expected to experience the most extreme prison peer effects. Longest-duration cellmates were chosen because they were expected to exert the most extreme prison peer effects. The prevalence of rearrest and recidivism (i.e., rearrest or reincarceration without rearrest) were chosen because they are the most directly related to the act of reoffending, with the least amount of intervention by the criminal justice system. Each of these choices limits either the internal or external validity of the findings.

First-time releasees. In 2006 and 2007, 17,582 unique prisoners were released from PADOC custody. Of those, 12,494 were first-timers.[46] 71.06% of the prisoners released from PADOC custody in 2006 and 2007 were, therefore, first-time releasees. Still, the findings reported by the current study are generalizable only to first-time prison

[46] Of those, 10,131 were admitted to PADOC custody on or after January 1, 2000.

inmates, who make up only a little more than two-thirds of the population of inmates released from PADOC in 2006 and 2007. Thus the failure to find average criminogenic effects in this sub-population still allows for the possibility that peer effects could be, on average, criminogenic if the whole population were covered. Expanding the sample of PADOC first-time releasees to include all of the members of the release cohort (i.e., adding in the re-offenders) would allow for comparisons between the impact of prison peers on the reoffending outcomes of first-time and returning prisoners.

Longest-duration cellmates. The cellmates with whom releasees shared a cell for the most days were theorized to exert greater prison peer effects than other cellmates. Per Sutherland (1947), relationships that last longer should yield larger social interaction effects (Agnew, 1991; Warr, 1993; Haynie et al., 2005). This choice had consequences for the cellmate association duration thresholds that could feasibly be investigated. For example, most releasees spent more than one month with their cellmates, so meaningful comparisons could not be drawn between those releasees who spent at least a month with their cellmates and those who did not. It may be possible, though contrary to theory, that shorter-duration associations produce more meaningful effects. In the prison context, for example, cases of "negative adjustment" that require immediate moves due to one inmate victimizing another might be expected to generate large, cascading, criminogenic effects (Adams, 1992; personal communication, 2013).

Other choices related to which cellmate associations were examined may also have been consequential. Although the timing of the onset of the longest-duration cellmate association relative to the releasees' prison stays did not seem to significantly affect reoffending outcomes, cellmates other than the longest-duration cellmates might be more relevant to releasee reoffending. In particular, Clemmer (1940) ascribed importance to first cellmates because inmates "seem to rely greatly on [their] first impressions of people" and the "first contacts" that they make in prison (p. 100).

Last cellmates might also be especially relevant. The peak-end rule suggests that the most intense and the most recent experiences are the most salient (Kahneman et al. 1997; Kahneman, 2011). This implies that last cellmates might exert greater peer influence than other cellmates, although whether those effects should be criminogenic or crimino-suppressive is unclear. Glaser and Stratton (1961) hypothesized that inmates tend toward different associations during different periods (early, middle, and late) of their prison stays, such that inmates seek more prosocial influences as they approach their release dates. Crewe (2007) reported pre-release behavioral improvements in line with this expectation, which was also confirmed by PADOC staff members who reported housing sex offenders, who are at higher risk for victimization, with inmates who are near their release date (personal communication, 2013). These pre-release behavioral anomalies on the part of both inmates and correctional officers may create particularly artificial cellmate relationships that either fail to generate appreciable social interaction effects, fail to generate social interaction effects that persist beyond incarceration (Giordano, 2003), or generate crimino-suppressive rather than criminogenic effects.

The problem with the hypothesis that other cellmates might exert greater influence over releasee outcomes than do the longest-duration cellmates is that the PADOC data do not reflect that potential. The collective contribution of the cellmate pool, exclusive of longest-duration cellmates, was generally inconsequential to reoffending after the influence of the longest-duration cellmates was controlled.

Moreover, as shown in Table 7, most characteristics of the longest-duration cellmates did not affect releasee reoffending independently. These results may cast some doubt on prior prison peer evidence based on facility-level effects aggregated from individual offending histories (e.g., Bayer et al., 2009). However, it is important to note, once again, that the current study did not include measures of the types of criminal behavior in which the releasees and their cellmates engaged prior to incarceration, whereas those criminal behaviors were the focus of the Bayer et al. (2009) inquiry. That difference could account for the disparate results.

Social interaction and outcome measures. The measures used to indicate criminal experience and criminality were the number of prior arrests, whether a cellmate had a prior incarceration, and a risk score based on PADOC's Risk Screening Tool. With respect to the social interaction variables, the risk score measure proved problematic methodologically. In addition, each of the social interaction variables is subject to similar conceptual problems.

The risk score was constructed from other measures in the PADOC data that remained significant to the determination of reoffending outcomes even when the risk score was included in the analysis. This suggests that the risk score does not predict outcomes as well as its constituent elements do. Moreover, its inclusion as a summary measure may unnecessarily introduce some collinearity into the model, although not so much that the models could not be estimated.

Each of the social interaction measures, which are intended to reflect criminal experience and/or criminality, is flawed in the context of criminological learning theories, particularly differential association theory, the constructs of which both prisonization and balance theories reference. The constructs that underlie differential association theory are more nuanced than the social interaction measures utilized in the current study.

Differential association theory expects definitions to motivate criminal behavior, but each of the social interaction measures is a behavioral measure. For example, the risk score measure is derived from of an actuarial assessment used widely by correctional administrators in Pennsylvania. While the risk score is, therefore, a measure of criminality employed by PADOC, it, not a true attitudinal measure of underlying criminality, as favored by differential association theory (Sutherland, 1947). Moreover, the non-demographic elements that comprise the risk score are behavioral, rather than attitudinal indicators of an individual's propensity to commit future crimes. Similarly, prior incarceration and prior arrest are behavioral indicators thought to reflect attitudinal differences. However, they may not serve that purpose, particularly given their reliance on the agency of the criminal justice system for measurement, as will be discussed in more detail below.

Differential association theory also expects different definitions to motivate different crimes. Unlike Gottfredson and Hirschi (1990), Sutherland (1947) did not subscribe to the notion of a general theory of crime. In contrast, the recidivism risk, prior incarceration, and prior arrest measures reflect general seriousness or frequency in offending, but do not capture the subtler differences in various types of criminal behavior (e.g., expressive or instrumental, violent or non-violent). Moreover, while they do capture differential criminal behavior in terms of volume (Warr & Stafford, 1991) and while they had previously been shown to be related to prisonization processes (Wheeler, 1961; Wellford, 1973), the prior incarceration and prior arrest measures, in particular, do not capture the hypothesized differences definitions or attitudes that incite those behaviors (Sutherland & Cressey, 1955; Matsueda, 1988).

Similarly, the dichotomous outcome measures are blunt measures of reoffending, both conceptually and operationally. As described in Chapter 4, the rearrest and recidivism measures are official measures that reflect some intervention of the criminal justice system in addition to reoffending. Moreover, because they are binary measures they only capture whether a releasee's apparent attempt to reoffend was detected and sanctioned by the criminal justice system: nothing more nuanced than that is recoverable. The rearrest and recidivism measures, therefore, are not just measures of individual reoffending behavior, they also measure whether that reoffending was sanctioned by the criminal justice system.

The individual and institutional elements of the reoffending measures cannot be separated (Maltz, 1984). The implications of the inability to decompose the reoffending measures into individual behavior and the agency of the criminal justice system are discussed more thoroughly in the context of the differences between the rearrest and recidivism outcomes, below. They can be summarized as such: the reoffending measures may poorly reflect actual offending behavior, which may limit their utility as indicators of prison peer influence.

The reoffending measures are also dichotomous. While dichotomous offending measures, particularly for outcomes, are the most frequently used measures in the criminological literature, Sweeten (2012) argued that they are the "simplest and weakest" (p. 542) measures of offending because they ignore "all seriousness and frequency of offending" (p. 552). Dichotomous measures weight less serious offenses the same as more serious offenses. Outcomes based on them are, therefore, potentially driven by more frequent, minor crimes. For these reasons, Sweeten (2012) further recommended that dichotomous measures "should only be used if they are shown to be robust to known methodological shortcomings" (p. 554).

Unlike the aforementioned conceptual concerns that do apply to the social interaction measures, Sweeten's (2012) concerns related to the dichotomous operationalization of the outcome variables do not appear to apply to the reoffending measures used in the current study. With respect to frequency, most of the PADOC releasees who were rearrested (n=5,938), were only arrested once (n=2,637) and only about 10% were arrested more than three times. There is, therefore, very little variation in reoffending frequency to exploit for the purposes of effect identification. With respect to the seriousness of the criminal activity of those releasees who were arrested, only 718 releasees were not arrested for a drug, property, or violent crime. These primary offense types are not trivial offenses in this dataset, as can be seen in the appendix to this chapter. Moreover, official measures like arrest are likely to underreport criminal activity (Maltz, 1984; Thornberry & Krohn, 2000). It is, therefore, reasonable to capture these potentially less serious events to more accurately measure the prevalence of reoffending in the release cohort.

With respect to the reincarceration without rearrest cases, which seem to be driving the significant findings, there is also little variation in frequency to exploit. The vast majority of releasees are either not recommitted (n=5,440) or only recommitted once (n=3,244). With respect to the reincarcerating event itself, differentiations were not made with respect to the type of reincarceration (e.g., whether the reincarceration resulted from a new court commitment or a parole violation). That is, the seriousness of the reincarcerating offense was not captured. It is also unclear whether it could be captured, as strong assumptions would need to be made regarding the nature of parole violations, in part because the type of violating offense is not recorded in the PADOC data. Inmates who are recommitted without being rearrested appear in the data under the original offense(s) for which they were committed. Moreover, as Grattet et al. (2009, 2011) found in California, some parolees who have committed serious offenses are recommitted as parole violators without being tried for these new crimes, a practice known as back-end sentencing.

In sum, like the social interaction measures, the outcome measures lack subtlety, particularly given the rich criminological context in which criminal behaviors and attitudes are expected to be transferred from inmate to inmate via ordinary learning processes, such as dialogue, modeling, punishment and reinforcement (Clemmer, 1940; Sutherland, 1947; Burgess & Akers, 1966; Matsueda, 1988; Akers, 2009). As noted in Chapter 4, Matsueda's (1988) critique of the differential association literature applies to the current study: attitudes and definitions are not observed. Only behaviors are. Furthermore, those behaviors are broad reoffending measures, not nuanced measures of criminal proclivities that might be reflected in offense descriptions and crime types (e.g., Bayer et al., 2009). Finally, the reoffending measures confound the behavior of individuals and the behavior of the criminal justice system. These shortcomings with respect to the construct validity of the social interaction variables and the outcome variables imply that, while the current study has been motivated by criminological theory, it is not an adequate test of it.

Dichotomous outcomes in the LIV framework. In addition to their failure to fully capture criminological constructs in a differential association framework, the dichotomous outcome measures are problematic in the context of the LIV method, which expects a dichotomous exclusion restriction, but continuous outcome measures. Applying continuous models to dichotomous outcomes is common in the treatment effect literature (Brock & Durlauf, 2001, 2007; Angrist & Pischke, 2009; Dong & Lewbel, 2012; Chesher, 2010; Chesher & Rosen, 2013). Moreover, Angrist and Pischke (2009) argue that the dichotomous nature of the outcome variable is inconsequential when estimating marginal effects, as is done in the LIV method, because the area over which the estimation occurs is so minute.[47] However, Dong and Lewbel (2012) show that there are cases where the choice of a binary, rather than a continuous, outcome does impact results.

The current study does not appear to be a case similar to the one simulated by Dong and Lewbel (2012). The generally null results from the *ivprobit* model, which does employ the correct functional form assumptions with respect to the outcome and instrumental variables, mirrored the null average prison peer effects estimated via local instrumental variables.[48] Nevertheless, an extension of the LIV framework to

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[47] In his explication of the IV method for application to criminological randomized controlled trials, Angrist (2006, p. 35) goes further, "Whenever you have a complete set of dummy variables on the right hand side of a regression equation (a scenario known as a saturated model), linear probability models estimate the underlying conditional mean function *perfectly*…You cannot improve upon perfection" (emphasis in original). This was true in the current analysis: the facility fixed effects are a complete set of dummy variables.

[48] In the context of the null LIV estimates at each duration threshold examined, the single significant coefficient on duration in the *ivprobit* specifications is curious. It may be that the *ivprobit* results, which do not account for essential heterogeneity, were biased. It may also be that the choice of duration thresholds, though theoretically and methodologically motivated was poor. These hypotheses can be explored in future work.

dichotomous outcomes or the choice of continuous outcome measures would improve the internal validity of the estimation process.

Divergence between rearrest and recidivism outcomes. Despite the lack of subtlety in the outcome measures, the analysis based upon them did reveal an interesting puzzle. Although the LIV-estimated prison peer effects were insignificant for both rearrest and recidivism, aspects of the preliminary analyses suggested that peer influence impacts each reoffending measure differently. In the baseline linear probability models, recidivism was more significantly affected by prison peer influence than was rearrest. Moreover, in the more appropriate specifications (IV and LIV), the average peer prison peer effect estimates were likelier to be significant or close to significant for recidivism outcomes, whereas estimates for the rearrest outcomes never approached significance.

The factors that predict rearrest and recidivism also appear to differ. In the LPM models, the homophily variables were collectively significant to rearrest, but not to recidivism, while the facility fixed effects appeared collectively significant to recidivism, but not rearrest. Similar differences emerged for individual predictors such as the releasee's time to release, prior employment, and maximum sentence, as well as for the cell characteristics (e.g., tier). These differences between the average prison peer effects estimated for each outcome suggest, first, that recidivism is more subject to prison peer effects than is rearrest and, second, that the processes that generate these outcomes differ.

Only the inclusion of those who were reincarcerated without being rearrested in the recidivism measure differentiated the two outcomes measures. And, only 877 releasees were reincarcerated without being arrested. These individuals, who comprise only 8.66% of the release cohort, therefore, appear to be driving the difference between the rearrest and recidivism estimates.

That social interaction effects are known to be highly context and outcome dependent may explain the observed differences between the rearrest and recidivism models (Hartup, 2005; Brechwald & Prinstein, 2011; Horney et al., 2012; Sacerdote, 2014). For example, Sacerdote (2014) noted that peer effects in education are modest, whereas they can be substantial for non-academic outcomes, such as drinking and delinquency (e.g., Glaeser, Sacerdote, & Scheinkman, 1996; Duncan et al., 2005). Additionally, within the exclusive study of criminal and delinquent behaviors, outcomes have been shown to depend heavily on context (Horney et al., 2012), with situational elements thought to play a significant role in the production of criminal behavior (Osgood et al., 1996). However, finding that peer effects vary with the contexts in which behaviors arise and propagate or that they vary depending on the types of behaviors examined is far different than finding that two related measures of similar behaviors appear to yield dramatically different effects.

Prevalence of rearrest and recidivism are typically conceptualized as contextually similar: they are two measures of underlying reoffending behavior (Maltz, 1984). As such, they should be positively correlated. However, in the current study, they were not. In fact, although the results were insignificant, with respect to relative prior arrests, rearrest evinced the expected increase in average prison peer effects as a result of interacting with more criminally experienced cellmates, while average prison peer effects on recidivism unexpectedly appeared to decrease with respect to increasing positive differentials in relative prior arrest. Neither relationship suggested the presence of the balancing effects (positive effects associated with positive risk scores, negative effects associated with negative risk scores) expected by McGloin's (2009) theory.

The etiology of rearrest versus the etiology of reincarceration. Explaining the divergence in the average prison peer effects associated with the rearrest and recidivism outcomes would strain current criminological conceptualizations of peer influence. While Sutherland (1947) did not expect different crimes to have similar etiologies, it is doubtful that he would argue that one measure of general criminal involvement should differ from another, such that they do not at least point in the same direction. It may, therefore, be the case that, for some releasees, learning processes are overwhelmed by other mechanisms.

Criminological explanations that do not rely on learning theories might better explain the seemingly disparate, although insignificantly so, outcomes for rearrest and recidivism. The differences in the rearrest and recidivism outcomes might, for instance, reflect the changing nature of the probability of being reincarcerated for a new crime (Grattet et al., 2009, 2011).

In his careful consideration of potential recidivism measures, Maltz (1984) concluded that rearrest is the measure most likely to reflect true reoffending behavior primarily because it involves the least successive steps of the criminal justice system. Concurrently, the role of the criminal justice system in the production of reoffending was subject to empirical exploration (e.g., Farrington, 1977; Petersilia & Turner, 1990). In an instructive study, Petersilia and Turner (1990) found, contrary to their expectation that intermediate sanctions might reduce reoffending (Petersilia & Turner, 1989), that more intensive supervision of probationers yields more reoffending. They attributed this counterintuitive finding to an increase in the probability of detection of ongoing criminal behavior due to the intensive supervision.

Similarly, the releasees in the current sample who were reincarcerated without being rearrested may have been subject to stricter supervision regimes than the releasees who were rearrested. Approximately 85% of the 2006-2007 first-time PADOC releasees were released on parole, which accords with the national numbers (Maruschak & Bonczar, 2013). As has been the case nationally, a substantial number of the PADOC releasees appear to be returned to prison, both after committing new crimes and for technical violations.

The trend toward recommitting technical parole violators creates a revolving door from the prison to the community and back again that does not necessarily require an arrest (Useem & Piehl, 2007; Raphael & Stoll, 2009; Grattet et al., 2009, 2011). Paroled drug offenders can be recommitted, without having been arrested, for failing mandatory drug tests administered by their parole officers and for absconding (Hawken & Kleiman, 2009; Bonczar, 2008). Parolees can also be recommitted for non-criminal behaviors such as failing to maintain employment. A potentially greater concern is the commonality of "back end sentencing" (Grattet et al., 2009, p. 10) of criminal offenses, which appears to have supplanted new prosecutions in California and, potentially, in Pennsylvania. Grattet et al. (2009, 2011) found that California parolees who had committed new crimes were often remanded immediately to correctional custody rather than compelled to face a new prosecution, a practice which both obfuscates these offenders' true criminal records and escalates the process of reincarceration.

In short, the how and why of reincarceration may appear to differ markedly from the how and why of rearrest, not because reoffending differs, but because the detection of that reoffending differs. These potential differences between the processes that generate each reoffending measure are currently poorly understood, but there are indications that those differences exist, both in the prior literature and in the current study.

Importantly, the differences in the etiologies of rearrest and recidivism might signal that official measures of reoffending are too noisy (i.e., so polluted by the agency of criminal justice system actors) to serve as accurate measures of individual behavior. Moreover, if official measures do not accurately reflect individual behavior, they also cannot serve as indicators of peer influence. Whether and how the processes that result in rearrest and reincarceration differ and whether and how they might have obfuscated the prison peer effect estimates in the current study are, therefore, important questions for future research.

Theoretical Limitations

According to the descriptive statistics presented in Chapter 6, cellmates in the current study were, on average, more criminally experienced, as measured by their prior incarceration and prior arrest histories, and exhibited more average criminality, as measured by their RST scores, than the first-time releasees. Average criminogenic prison peer effects were expected, but null average prison peer effects were detected. While this outcome contradicts the expectations of differential association (Sutherland, 1947), balance (McGloin, 2009), and prisonization (Clemmer, 1940, 1950) theories, strong conclusions with respect to those theories cannot be made due to the inability to construct attitudinal criminality measures from the administrative data. However, that behavioral measures, which have been used to evaluate peer effects (Warr & Stafford, 1991; Pratt et al., 2010), evinced such little variation in average prison peer effects suggests that other processes may better explain the failure of incarceration to reduce reoffending.

Other mechanisms. That prisons can be learning environments (Bentham, 1830; Clemmer, 1950) is only one means through which the assumed specific deterrent effects of imprisonment might be subverted. As was discussed in Chapter 2, harsh prison environments may lead to defiant post-prison responses that excite reoffending (Sherman, 1993; Gendreau, Goggin, & Cullen, 2000; Toch, 2001; Mears, 2014; Winerip & Schwirtz, 2014). Alternatively, the apparent failure of incarceration to reduce reoffending may owe less to what happens to people in prison and more to what happens to people after they are released from prison (Travis, 2005; Blumstein & Nakamura, 2009; NRC, 2014.). Labeling processes and the resultant social and institutional stigmatization of those who have been incarcerated may better account for the enduring deleterious effects of incarceration (Lemert, 1951; Pager, 2003; Pettit & Western, 2004). Similarly, institutionalized political and societal post-prison disenfranchisement may stymie reintegration processes (Travis, 2005; Lattimore & Visher, 2009; NRC, 2014). Finally, increased surveillance by the criminal justice system may account for a significant portion of the prevalence of rearrest and, in particular, reincarceration (Petersilia & Turner, 1989, 1990; Grattet et al., 2009, 2011).

Is there specific deterrence to subvert? The preceding section argued that, if the failure of incarceration to reduce reoffending reflects a failure of specific deterrence, as suggested by Nagin et al. (2009), mechanisms other than social influence during incarceration may better account for that failure. There is, of course, another possibility:

specific deterrence may not have failed; the presumption that there are specific deterrent effects to subvert may be false.

Nagin et al. (2009) attempted to establish that deterrence as a result of incarceration is a real phenomenon. However, the studies that they cited as paying particular attention to the counterfactual that incarceration has a null specific deterrent effect (Helland & Tabarrok, 2007; Drago et al., 2009) are potentially paying particular attention to the wrong counterfactual (Heckman & Urzua, 2010).

Two of the strong studies reviewed by Nagin et al. (2009) pay careful attention to the potential deterrent effects of incarceration. They demonstrate that the threat of twenty-five years in prison is a strong deterrent (Helland & Tabarrok, 2007) and that the threat of having to serve a residual sentence after early release from prison is also a substantive deterrent to future criminal behavior (Drago et al., 2009). However, the threat of punishment is different than the experience of it, just as being committed to prison for a particular amount of time is not the same as being released early from prison due to an exogenous policy shift (e.g., Levitt, 1996). As Heckman and Urzua (2010) noted in their criticism of the treatment effects literature more generally, IV strategies often fail to address the exact policy question of interest. That seems to be the case with respect to the studies reviewed by Nagin et al. (2009). Those studies fail to address the key question of interest: Does the experience of incarceration affect reoffending? In so doing, they, therefore, also fail to definitively demonstrate that specific deterrent effects contribute to null prison effects.

If incarceration has a null, instead of a presumed and rather large specific deterrent effect on reoffending (e.g., Nagin & Snodgrass, 2013), the null prison peer effect findings from the current study make sense. In the proverbial law of averages, positive effects and negative effects balance. In samples, however, positive and negative effects may emerge by chance, a tendency that may account for the previously reported modest prison peer effects (Bayer et al., 2009) as well as the equally modest peer effects reported in the extant literature (Angrist, 2013; Sacerdote, 2014).

Questions Asked and Answered: A Story of Average Effects Becomes a Story of Marginal Effects

The main insight to come from this study is that productive lines of inquiry into prison peer influence are unlikely to proceed from asking and answering questions related to average effects. Put simply, average prison peer effects neither adequately nor accurately characterized prison peer effects for many first-time releasees from PADOC. That statement is not meant to imply that there are no prison peer effects. Instead, what is clear is that there is considerable variation in prison peer effects, such that a single, average measure fails to characterize those effects for many prison peers.

Considerable response heterogeneity was evident in the marginal prison peer effect estimates. Response heterogeneity is endemic to the social sciences (Heckman, 2000) criminology (Loughran & Mulvey, 2010), and to the study of social interactions, in particular (Durlauf & Ioannides, 2010; Graham, 2011; Sacerdote, 2014). In the context of the current study, response *homogeneity* would mean that the effect estimates would show that observationally similar releasees respond to observationally similar cellmates in observationally similar environments in observationally similar ways. That did not happen. While most of the members of the PADOC first-time release cohort experienced no discernible prison peer effects, some releasees appeared to experience criminogenic prison peer effects, and others appeared to experience crimino-suppressive prison peer effects.

Definitive conclusions pertaining to the marginal prison peer effects themselves are imprudent to draw given the thinner subsamples at the tails of the propensity score distribution where the significant MPPEs emerged. Nevertheless, the LIV analysis provided strong evidence that cellmate associations may benefit some inmates, even as they harm others: not one of the dozens of marginal prison peer effect curves is horizontal. Moreover, the finding that MPPEs are relevant at the tails of the propensity score distribution echoes Wellford's (1973) conclusion that behavioral shifts due to attitudinal change are evident only at "orientational extremes" (p. 115).

Marginal prison peer effects isolated via the LIV method are reported as a function of the propensity not to remain in lengthy cellmate associations. In the LIV framework, marginal prison peer effects and, more generally, marginal treatment effects, are framed in this way to highlight the role played by the unobserved determinants of treatment (i.e., duration of association with criminogenic cellmates) in generating the observed response heterogeneity of the releasees. The ability to characterize the collective effect of all the unknown factors that determine outcomes is a unique strength of the LIV method. Other methods do not offer the ability to characterize the unobservables separately or collectively.

The current analysis evinced considerable response heterogeneity in the relationship between cellmate social interactions and reoffending. When releasees stay in long-term cellmate associations for unobserved reasons, they experience criminogenic effects. When, for unobserved reasons, releasees do not stay in long-term cellmate associations, they experience crimino-suppressive effects. Marginal prison peer effects vary even though average prison peer effects do not.

The response heterogeneity in the marginal prison peer effect estimates is attributable to essential heterogeneity. Importantly, the presence of essential heterogeneity, which is implicitly theorized to bias criminological studies of social influence, was detected despite the inclusion of *more* "statistical controls for selection" than "those in any previous research on peer effects" (Haynie & Osgood, 2005, p. 1119). Yet, the presence of essential heterogeneity means that critical information about the determinants of the cellmate association longevity decision and the outcomes theorized to result from it remained unobserved.

The essential heterogeneity detected in the current study can potentially, but not definitively, be attributed to many factors. The unobserved determinants of the length of the cellmate association are likely to include unobserved elements of the releasee's decision, unobserved components related to the agency of cellmates and correctional officers, and unobserved elements of the prison context. To better understand the relationship between cellmate associations and reoffending outcomes, these unobserved factors need to become better understood. Given their absence from the current study, attitudinal measures may be good candidates for future exploration, particularly where they are extreme (Wellford, 1973).

Future Directions

The null average prison peer effect findings reported by the current study were surprising. If evidence from future studies continues to confirm that average prison peer effects are null, it will contradict hundreds of years of criminological theory and evidence, which overwhelmingly predicts that social interactions that take place in prison will have criminogenic effects on prisoners, primarily because less experienced criminal encounter more experienced criminals in prison (Bentham, 1830; Clemmer, 1940; Bayer et al., 2009; Nagin et al., 2009). If it does not, this study will stand as an anomaly.

Overcoming limitations. The preceding discussion illuminated several potential limitations of the current analysis. The first future steps to be taken therefore involve overcoming them. First, a larger sample of first-time releasees can be identified. A larger sample would likely allow for more accurate effect identification, particularly at the extreme regions of the propensity to <u>not</u> enter into lengthy cellmate relationships, which is where marginal prison peer effects appear most likely to have non-null effects. If a larger sample cannot be taken, a more complete application of the local instrumental variables framework can be used to estimate the effect of treatment on the treated, as described below.

Second, more nuanced social interaction and outcome measures that better reflect the attitudinal constructs central to criminological theory can be created by better exploiting the arrest history information provided by the Pennsylvania State Police and the institutional testing data from PADOC. Through more nuanced criminality and criminal experience measures, it may be possible to isolate changes in offending behavior that are subtler than prevalence, which is a weak measure (Sweeten, 2012). For example, shifts in the versatility and specialization of offending may be detectable (Farrington, Snyder, & Finnegan, 1988; Bayer et al., 2009; Sullivan & McGloin, 2014). Moreover, as described in the section on the potential for theory testing below, better measures of the inmates' criminality may be available from PADOC.

Third, cellmate relationships other than the longest-duration cellmate can also be explored. First and last cellmates might have particular importance in the evolution of inmates' prisonization processes (Clemmer, 1940; Jones & Schmid, 2000; Kahneman et al., 2011). Peer groups may also prove relevant, although they did not seem to be in the current analysis (Rees & Pogarsky, 2011). Fourth, effects on other releasees can also be explored. While the first-time releasees are theorized to be more susceptible to social influence in the prison environment than more seasoned inmates (Wheeler, 1961; Nieuwbeerta et al., 2009), whether they actually are or not remains an untested empirical matter. Extending the first-time release cohort to include non-first-timers would allow for an empirical investigation of this decades-old assumption, while also allowing for more general prison peer effect estimates.

Finally, the LIV framework can be formally extended to better reflect the reality of social interactions: it can be extended to include characterization of multiple decision makers (and the unobserved heterogeneity attributable to each) and to account for binary outcomes. Work by Graham (2011), Brock and Durlauf (2001, 2007), and Chesher & Rosen (2013) exemplifies the ways in which these extensions might be possible. For a review, see also Durlauf and Ioannides (2010).

Extending the analysis. The current study introduced the concept of essential heterogeneity and the method of local instrumental variables to criminology. It did not, however, offer a full exposition of every element of the LIV method. Through identification of the marginal treatment effect parameters all other treatment effects can be identified, not just average treatment effects (Heckman & Vytlacil, 1999, 2000, 2001; 2005; Basu et al., 2007). For example, local average treatment effects, policy-relevant treatment effects, and the effect of treatment on the treated can be identified. Furthermore, those effects can be identified even when the support of the propensity score is not full by deriving sample-dependent weights to the convert the MTEs to other treatment effect parameters, as shown in Heckman and Vytlacil (2005, p. 680-681).

The effect of treatment on the treated (TOT), in particular, may be important to understanding variation in prison peer effects, beyond their null averages. Operationally, in highly segregated prison environments, pairing releasees and cellmates with particular characteristics might be rare (e.g., Harvard Law Review, 2004; Trulson, Marquart, Hemmens, & Carroll, 2008). Such pairings might also be particularly consequential in determining average outcomes if they generate large criminogenic or crimino-suppressive effects. To examine the effects of these pairings, TOT parameter estimates might be helpful. As illustrated in Basu et al. (2007), TOT estimates are useful when support of the propensity score is not full, as it might not be for rarer pairings. Furthermore, TOT estimates might also be useful if a larger sample of PADOC releasees cannot be taken or if taking that larger sample again fails to produces adequately-sized comparison groups at the extremes of the propensity score distribution.

Extending the application of the analysis. Heckman and Vytlacil (2005) point to three “central tasks” of their research. Those tasks, “evaluating the impacts of public policies, forecasting their effects in new environments, and predicting the effects of policies never tried” (p. 669), illustrate the potential of the LIV method, particularly for prison peer research.

Incarceration is, for better or for worse, a common public policy that will impact the lives of the millions who experience it and the lives of millions more who are connected to those who experience it (NRC, 2014). Within prisons, decisions that create cellmate associations determine which inmates will be prison peers and for how long. While formalized policies do not appear to govern those decisions in the PADOC system, those informal decisions have consequences, just as if they were codified. The primary goal of the current study has been to determine the effects of those celling decisions. On average, those effects appear null. At the margin of the *probability of remaining with a cellmate,* however, some inmates are affected positively by their cellmates in that they are less likely to reoffend after associating with them and some are affected negatively by their cellmates in that they are more likely to reoffend after associating with them.

A central task for future prison peer research will be to gather more knowledge regarding inmate and institutional celling preferences and to apply that knowledge to predict the effects of potential housing policy shifts, just as researchers are now attempting to prospectively predict the effects of potential sentencing policy shifts (e.g., Reitz, 2009). However, as this is the first study to apply the LIV method to the study of social interaction effects in any context, it is prudent to echo Sacerdote's (2014) caution regarding peer allocations, while also illuminating a unique potential of the LIV method as it pertains to the possibility of (eventually) formulating and testing policies intended to alter prison peer effects on reoffending.

Sacerdote (2014, p. 1) cautioned against the temptation to recommend policies to reallocate peers to manipulate peer effects. "[D]espite potential temptation," he wrote, "we have not reached the point at which we can reliably use knowledge of peer effects to implement policies that improve outcomes for students and other human subjects" (e.g., Carrell, Sacerdote, & West, 2013). That temptation is, however, the potential to which policymakers aspire and a research goal to which Heckman and Vytlacil (2005) implicitly referred.

The local instrumental variables framework offers a means through which the potential to reduce, or at least not exacerbate, reoffending through cellmate assignments may become possible. To work toward that goal, more information about the individuals to whom particular policies apply and the particular effects to which they are subject can be extracted from applications of the LIV method than can be extracted from the application of other estimation strategies, such as ordinary least squares regression or instrumental variables techniques.

In addition to enhancing the potential for econometric analyses to generate the knowledge necessary to make prison peer allocation decisions, the LIV framework offers a means through which such allocations can be prospectively tested (Heckman & Vytlacil, 2005). In contrast to ordinary IV techniques, such as 2SLS, which difference out levels in order to identify gains, the individuals to whom particular marginal treatment effects apply can be identified in an LIV implementation. If definitive trends emerge within the observable information to suggest that some prisoners are routinely harmed by particular cellmate pairings, whereas other prisoners are not, it may be possible to avoid those harmful pairings.

The potential for theory testing. Were the current study a true test of criminological learning theories, it would offer them little support. Although, as is implicit in criminological learning theories, essential heterogeneity was shown to be present in the relationship between social interactions with cellmates and reoffending, the estimated average prison peer effects did not accord with the expectations of the criminological learning theories (i.e., differential association, balance, and prisonization) used to motivate this study. By each of the three measures of criminality and criminal experience, the cellmates of the first-time releasees were, on average, more criminogenic than the releasees. Still, evidence of average criminogenic prison peer effects did not emerge from any of the estimated models, at any of the examined duration thresholds.

While the current study relied on criminological learning theories for motivation, it was not a true test of those theories. The behavior-driven outcome, criminality, and criminal experience measures do not align well with the definitions described by Sutherland (1947) and relied upon by Clemmer (1940) and McGloin (2009), per Matsueda (1988). Moreover, official measures of reoffending reflect both individual behavior and the behavior of the criminal justice system to unknown degrees.

Future work can explore the means through which criminological theory might better be tested using data that may be available from PADOC. The PADOC data are still being explored and developed for research purposes, which means they can be developed for particular research purposes, such as theory testing. For example, a true test of McGloin's (2009) balance theory would require outcome data for both releasees and cellmates. To that end, prison misconduct data can be assembled such that prior and post cellmate association reoffending measures for both the releasees and their cellmates are present in the data. Alternatively, a sample comprised of only releasees with released cellmates could potentially be selected.

To better test differential association theory, attitudinal measures derived from answers to the individual LSI-R questions might be available from LSI-R tests, which have been more uniformly administered in recent years. The LSI-R is now used by both

PADOC at intake and by the Pennsylvania Board of Probation and Parole, so pre and post cellmate association criminality measures might be available for both releasees and their cellmates. Such measures would enable a more credible test of differential association theory (Matsueda, 1988).

Finally, whether developmental cascades lead to the persistence of prison peer effects over time has the potential to be explored via the PADOC data. Data on prison programming may be able to shed light on whether inmates are more likely to reoffend after interacting in intimate therapeutic groups. In therapeutic groups, iatrogenic effects may emerge as inmates discuss criminal behavior and, potentially, diminish the harm it is perceived to do to others. Increases in reoffending may emerge as inmates rationalize their behaviors through deviancy talk (Matza, 1964; Masten et al., 2005; Dodge et al., 2006; Dishion et al., 2010; Dishion, 2014).

Conclusion

The current study has sought to establish whether average prison peer effects can be held accountable for some portion of the failure of incarceration to reduce reoffending. The null average prison peer effects identified by the current study cannot account for prison effects that appear, on average, criminogenic.

Within the null average prison peer effects estimated lies tremendous variation in marginal prison peer effects. Some MPPEs appear to exert significant criminogenic effects on reoffending. Others appear to exert crimino-suppressive effects.

That substantial variation in the estimated marginal prison peer effects remained despite the inclusion of numerous controls suggests the potential for bias in previous peer effect estimates, in prison and other contexts, which relied on less robust methodology and/or employed fewer controls. Variation in the marginal prison peer effect estimates also points to an explanation for the modest and context-dependent social interaction effects estimated through robustly designed studies: unbalanced samples can yield biased and conflicting estimates.

This study was the first to examine prison peer effects in an adult prison population in the United States. Institutional, demographic, and criminal history information were collected from the administrative databases of the Pennsylvania Department of Corrections and the Pennsylvania State Police to create a unique dataset in which the members of a first-time release cohort were matched to each of the cellmates with whom they shared a double cell.

This study introduced the concept of essential heterogeneity to criminology and is the first criminological study to apply the local instrumental variables method to explain offending behavior or social interaction effects. Essential heterogeneity is implicit in and endemic to criminological theories, particular those of social influence. Criminological theories of social influence expect unobserved factors such as criminality to affect the outcomes of decisions that affect criminal behavior both independently and through those decisions.

The local instrumental variables analysis illustrated the role that essential heterogeneity plays in the determination of the impact of prison peers on reoffending. That illustration suggests that, given the current state of knowledge regarding prison peer effects and social interaction effects, more generally, it is more useful to study prison peer effects in marginal, rather than average, terms. Too many factors that determine how releasees respond to their cellmates are unknown. Moreover, the collective distribution of those unobservables appears balanced in the propensity to <u>not</u> be treated. Future work on prison peer effects should focus on the development of subtle measures that more accurately capture criminological concepts and on determining who is harmed and who is helped as a result of interactions with prison peers.

TABLES

Chapter 4 Tables

Table 1. Cross-tabulations of the prevalence of arrest (rearry4), the prevalence of incarceration (has_postI), and the prevalence of any recidivism (reincy4)

```
. tab rearry4 has_postI

     (sum) |       has_postI
   rearry4 |         0          1 |     Total
-----------+----------------------+----------
         0 |     3,775      1,139 |     4,914
         1 |     1,665      3,552 |     5,217
-----------+----------------------+----------
     Total |     5,440      4,691 |    10,131

. tab reincy4 has_postI

           |       has_postI
   reincy4 |         0          1 |     Total
-----------+----------------------+----------
         0 |     3,775          0 |     3,775
         1 |     1,665      4,691 |     6,356
-----------+----------------------+----------
     Total |     5,440      4,691 |    10,131

. tab reincy4 rearry4

           |     (sum) rearry4
   reincy4 |         0          1 |     Total
-----------+----------------------+----------
         0 |     3,775          0 |     3,775
         1 |     1,139      5,217 |     6,356
-----------+----------------------+----------
     Total |     4,914      5,217 |    10,131
```

Chapter 5 Tables

The tables associated with Chapter 5 appear starting on the following page.

Table 2. Characteristics of Pennsylvania's state correctional institutes that house males, 2000-2007.

Characteristics of Pennsylvania Department of Corrections Male Facilities, 2000-2007															
	General Characteristics				Population		% Capacity		Industry and Select Programs					
SCI	Open	Close	Square Feet	Level	2000	2007	2000	2007	Prison Industry	DV Prevent	CBT/ Skills	Reentry or PV	Sex Off	TCU
Albion	1993		354K	4	1,958	2,295	160.5	120.8	1	1	1	1	1	1
Camp Hill	1941		721K	4	3,160	3,380	153.5	108.0	0	1	1	1	1	1
Chester	1998		91K	3	978	1,163	149.1	101.1	0	1	0	1	1	1
Coal Twp	1993		276K	3	1,657	1,864	171.9	116.5	0	1	1	1	1	1
Cresson	1987	2013	---	4	1,254	1,571	141.2	112.2	0	0	0	0	1	1
Dallas	1960		142K	3	1,807	2,090	146.7	119.4	1	0	1	1	1	1
Fayette	2003		294K	4	---	2,036	---	106.4	1	1	1	1	1	1
Forest	2004		316K	4	---	2,072	---	104.7	1	1	1	1	1	1
Frackville	1987		130K	4	1,000	1,106	139.5	122.9	1	1	1	1	1	1
Graterford	1929		444K	4	3,197	2,898	130.7	103.5	1	1	1	1	1	1
Greene	1993		388K	4	1,726	1,917	129.6	105.2	1	1	1	1	1	1
Greensburg	1969	2013	---	3	830	979	148.2	122.4	0	1	0	0	0	0
Houtzdale	1996		320K	3	1,807	2,293	148.1	120.7	1	1	1	1	1	1
Huntingdon	1889		2.9M	4	1,982	2,184	140.4	128.5	1	1	1	1	1	1
Laurel High	1996		468K	2	381	1,015	79.5	108.1	0	1	0	1	1	1
Mahanoy	1993		379K	3	1,961	2,290	160.7	113.9	1	1	1	1	1	1
Mercer	1978		260K	2	1,024	1,310	176.9	117.3	0	1	1	1	1	1
Pine Grove	2001		181K	3	---	703	---	106.7	0	1	1	1	1	1
Pittsburgh	1882		538K	3	1,772	799	116.0	53.3	0	1	1	0	0	1
Quehanna	1992		136K	1	225	455	97.8	98.5	0	1	0	1	0	0
Retreat	1986		180K	3	842	889	183.8	110.3	1	1	1	1	1	1
Rockview	1915		326K	3	2,109	2,109	198.6	124.1	1	1	1	1	1	1
Smithfield	1988		127K	4	1,208	1,225	185.3	122.5	1	1	1	1	1	1
Somerset	1993		360K	4	1,754	2,314	182.0	121.8	1	1	1	1	1	1
Waymart	1989		149K	2	1,191	1,278	101.0	95.4	0	1	1	1	1	1
Waynesburg	1985	2003	---	2	455	---	94.2	---	1	---	---	---	---	---
TOT/AVE					34,278	42,235	145.0	110.6	15	23	20	22	22	23

Table 3. Outline of the Daily Schedule at SCI Dallas

<u>Outline of the daily schedule at SCI Dallas</u>

0600: Wake-up

0630: Count clears

0830: Breakfast ends

1030: Yard time ends

1100: Count clears

1230: Lunch ends

1300: Count clears

1530: Yard time ends

1630: Count clears

1800: Bed moves take place

1830: Night yard time starts

Daylight ends: Night yard ends

2030: Shower time

2100: Lock up

2130: Count clears

2200: Lights out

Chapter 6 Tables

Table 4. Misconduct classifications for most unique charges.

PADOC Misconduct Classifications		
Misconduct Literal	**High**	**Low**
ARSON	A	A
ASSAULT	A	A
BODY PUNCHING, HORSE PLAY	C	E
BREAK RESTRICTION OR QUARANTINE	A	C
BURGLARY	A	A
DESTROY, ALTER, OR DAMAGE PROPERTY	B	C
ESCAPE	A	A
EXHORT BY THREAT OR BLACKMAIL	A	B
FAIL TO REPORT AN ARREST	A	B
FAILTO REPORT OFFENSE/CONTRABAND	B	E
FAIL TO STAND COUNT	B	D
FIGHTING	A	B
GAMBLING OR GAMBLING OPERATION	A	C
INDECENT EXPOSURE	A	C
KIDNAPPING/UNLAWFUL RESTRAINT	A	A
LOAN OR BORROW PROPERTY	B	D
LIE TO AN EMPLOYEE	B	D
MURDER	A	A
POSSESS CONTRABAND OR MONEY	B	B
POSSESS OR CIRCULATE A PETITION	A	C
POSSESS OR USE DANGEROUS SUBSTANCE	A	B
PRESENCE IN AN UNAUTHORIZED AREA	B	D
RAPE/INVOLUNTARY INTERCOURSE	A	A
REFUSE TO WORK OR ATTEND SCHOOL	B	C
REFUSE TO OBEY AN ORDER	B	B
RIOT	A	A
ROBBERY	A	A
SEX ACTS WITH OTHERS OR SODOMY	A	B
SEXUAL HARASSMENT	A	A
SMOKING WHERE PROHIBITED	C	E
TAKE FOOD FROM DINING	C	E
TATOOING/SELF-MUTILATION	A	C
THEFT OF SERVICES (I.E., CABLE OR OTHER)	B	B
THREATEN AN EMPLOYEE OR FAMILY	A	A
THREATEN ANOTHER INMATE	A	B
UNAUTHORIZED USE/MAIL OR TELEPHONE	B	C
USE ABUSIVE OR OBSCENE LANGUAGE	A	C
WEAR A DISGUISE OR MASK	A	B

Table 5. Adaptation of the RST using the current data.

Q	RST Question (Section B)	Adaptation	Max	R(n)	C(n)	R(%)	C(%)
1	Age at first arrest	18 or under at first arrest	1	3,521	3,481	34.75	34.36
2	Current age	Current age	2				
	0: 43 or older	*0: 43 or older*		2,485	4,224	24.53	41.69
	1: 25-43	*1: 25-43*		5,203	5,723	51.36	56.49
	2:24 or younger	*2:24 or younger*		3,731	3,020	36.83	29.81
3	Prior convictions	Prior arrests	2				
	0: 0 prior convictions	*0: 0-2 prior arrests*		2,641	2,484	26.07	24.52
	1: 1 prior conviction	*1: five or fewer arrests*		3,388	3,068	33.44	30.28
	2: 2+ prior convictions	*2: six or more arrests*		4,102	4,579	40.49	45.20
4	Misconducts	Convicted of AB misconduct	1	2,485	4,224	24.53	41.69
5	Violated community supervision	Has parole violation	1	0	0		
6	Education less than grade 12	Education less than grade 12	1	4,069	4,038	40.16	39.86
7	Alcohol or drug problem	Reported alcohol/drug problem	1	9,436	9,254	93.14	91.34
		Maximum Risk Score	**9**				

Table 6. Inmate characteristics for 10,131 releasees and 55,656 cellmates

	Releasees	All Cellies	Stable Cellies
Demographic Variables			
Age, years	30.3 (9.8)	33.1 (10.3)	31.57 (9.9)
Black	41.88	48.84	45.07
White	44.02	37.63	41.22
Latino	13.47	12.89	13.02
Other (Asian, Am. Indian, Other)	0.63	0.12	0.69
Married	13.59	14.11	15.49
Muslim	14.23	18.69	16.88
Catholic	19.71	17.97	19.17
Protestant	30.87	31.27	31.73
Jewish	0.47	0.58	0.51
No religion	20.91	17.13	17.25
Other	13.81	14.36	14.46
Served in US military	5.91	6.98	6.76
Committed from an urban county	75.59	78.96	78.96
Institutional History Variables			
Earliest custody Level > 3	23.2	28.64	23.83
Ever in administrative custody	1.84	18.2	23.36
Ever in therapeutic community	8.04	3.89	6.27
Institutional Testing Variables			
IQ	91.2 (13.9)	90.4 (14.8)	91.2 (14.6)
Has medical limitations	19.15	23.41	21.69
Reported employment before prison	24.78	38.3	34.91
Reported mental health problems	33.52	33.93	32.8
Sentence and timing			
Maximum sentence, months	63.1 (38.8)	112.6 (143.5)	114.5(144.6)
Time served, months	28.24 (18.8)	---	---
Three charges, recent arrest			
Risk score measures			
18 or under at first arrest	34.75	34.36	---
RST age	1.25 (0.65)	1.16 (0.64)	---
RST arrests	1.14 (0.80)	1.21 (0.81)	---
Ever convicted of AB misconduct	24.53	41.69	---
Violated supervision or escaped	0.00	14.84	---

Less than high school education	40.16	39.86	---
Reported alcohol or drug problem	93.14	91.41	---
Risk score total	4.52 (1.53)	4.79 (1.58)	---
Treatments and moderators			
Prior arrests	5.5 (4.3)	6.7 (5.8)	6.4 (5.6)
Has a prior incarceration	---	30.22	29.66
Relative arrests	0.86 (6.87)	---	---
Relative risk	0.27 (1.95)	---	---
Days in longest cellmate association	181.6(144.8)	---	---
Outcomes			
Rearrested within 4 years	51.50	---	---
Any CJS involvement within 4 years	62.74	---	---
Other variables			
Stretches	1.57 (1.06)	---	---
Releasee time to release	532.2 (430.40)	---	---
Releasee is also a cellmate	90.05	---	---
Cellmate is also releasee	---	16.39	23.98
Cellmates (n)	14.2 (9.3)	---	---
21 releasees have only one cellmate; Pool data is equal to single cellmate data for them			
16 releasees and 655 cellmates and 96 best cellmates have no RAP sheet: Their prior offending comes from PADOC records			
Other missing data is minimal: No releasees are missing covariates 151 cellmates are missing high school; 4 are missing military service.			

Chapter 8 Tables

Table 7. Choice and outcome models for rearrest and recidivism outcomes. Linear probability models estimated.

		Prior Arrest			Prior Arrest/RST	
		Choice: Duration	**Outcome: Rearrest**	**Outcome: Recidivism**	**Outcome: Rearrest**	**Outcome: Recidivism**
	Adj. R-squared	43.38	19.35	17.40	19.88	17.99
LRT	Releasee					
	Cellmate					
	Pool					
	Social Interaction					
	Other					
	Same					
	Facility Fixed					
	Instruments					
Duration	Time Together		-0.000080 (0.052)	-0.000103 (0.011)	-0.000074 (0.074)	-0.000095 (0.011)
Instruments	Cell Sq Footage					
	C Time to Releasee					
Social Interaction	C Prior Prison					
	R Prior Arrest					
	Relative Prior Arrest					
	R RST					
	Relative RST					
Releasee	Age					
	Black					
	Married					
	Islam					
	Urban					
	Max sentence					
	Custody Level					
	Misconducts					
	TC					
	Solitary AC					
	Three Charges					
	Under 18 First					
	Medical					
	HS Grad					
	Job					
	Drugs/Alcohol					

	Mental Health					
	US Vet					
	IQ					
Cellmate	Age					
	Black					
	Married					
	Islam					
	Urban					
	Max sentence					
	Custody Level					
	Misconducts					
	TC					
	Solitary AC					
	Three Charges					
	Under 18 First					
	Medical					
	HS Grad					
	Job					
	Drugs/Alcohol					
	Mental Health					
	US Vet					
	IQ					
	Violate Supervision					
Pool	Age					
	Black					
	Married					
	Islam					
	Urban					
	Max sentence					
	Prior Arrests					
	Custody Level					
	Misconducts					
	TC					
	Solitary AC					
	Three Charges					
	Under 18 First					
	Medical					
	HS Grad					
	Job					
	Drugs/Alcohol					
	Mental Health					
	US Vet					
	IQ					

	Prior Prison					
	Violate supervision					
	RST					
Other	Stretches					
	R Time to Release					
	Stay Length					
	Tier					
Same	Age					
	Race					
	Married					
	Islam					
	Urban					
	Custody Level					
	Misconducts					
	TC					
	Solitary AC					
	Three Charges					
	Under 18 First					
	Medical					
	HS Grad					
	Job					
	Drug/Alcohol					
	Mental Health					
	US Vet					
	IQ					
Facility base=ALB	CAM					
	CHS					
	COA					
	CRE					
	DAL					
	FRA					
	FRS					
	FYT					
	GRA					
	GRE					
	GRN					
	HOU					
	HUN					
	LAU					
	MAH					
	MER					
	PIT					

	PNG					
	RET					
	ROC					
	SMI					
	SMR					
	WAM					
	WAY					
	Key					
	Not significant					
	Significant					
	Not in model					

Table 8. Exclusion restriction tests output from *ivreg2* for both outcome models and both reoffending outcomes.

Outcome model #1. Four-year rearrest outcomes. *ivreg2* instrument tests.

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):            979.723
                                                  Chi-sq(27) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):         51.906
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    21.42
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        33.331
                                                  Chi-sq(26) P-val =    0.1527
```

Outcome model #1. Four-year recidivism outcomes. *ivreg2* instrument tests.

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):            979.723
                                                  Chi-sq(27) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):         51.906
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    21.42
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        36.262
                                                  Chi-sq(26) P-val =    0.0870
```

Outcome model #2. Four-year rearrest outcomes. *ivreg2* instrument tests.

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):            988.453
                                                  Chi-sq(27) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):         52.649
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    21.42
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        34.892
                                                  Chi-sq(26) P-val =    0.1140
```

Outcome model #2. Four-year recidivism outcomes. *ivreg2* instrument tests.

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):            988.453
                                                  Chi-sq(27) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):         52.649
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    21.42
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        37.240
                                                  Chi-sq(26) P-val =    0.0711
------------------------------------------------------------------------------
```

Table 9. Output from *ivprobit* for both outcomes models and both outcomes.

Social interaction variables and duration are highlighted in gray.

- Duration: total_tt
- Prior incarceration: c_hasPriorI
- Prior number of arrests: r_pri_narr
- Relative number of prior arrests: rel_pri_narr

Outcome model #1. Four-year rearrest outcomes. *ivprobit*.

Probit model with endogenous regressors	Number of obs	=	10131
	Wald chi2(86)	=	1897.57
Log likelihood = -67713.844	Prob > chi2	=	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
total_tt	.000326	.0003601	0.91	0.365	-.0003797	.0010318
r_age	-.0314991	.0019744	-15.95	0.000	-.035369	-.0276293
r_black	.1956599	.0498115	3.93	0.000	.0980311	.2932886
r_married	-.1297893	.0527524	-2.46	0.014	-.2331822	-.0263964
r_islam	.2470626	.0478336	5.17	0.000	.1533106	.3408147
r_urban	.0449779	.0369148	1.22	0.223	-.0273738	.1173297
r_maxsent	-.0044171	.0005004	-8.83	0.000	-.0053978	-.0034364
r_cust_gt3	.1197958	.0375857	3.19	0.001	.0461292	.1934624
r_misAB	.0862103	.0397384	2.17	0.030	.0083245	.164096
r_hadtc	.0169048	.0822565	0.21	0.837	-.1443149	.1781246
r_ever_ac_sol	.0130126	.0516192	0.25	0.801	-.0881591	.1141843
r_3charge	.0533947	.0288397	1.85	0.064	-.00313	.1099195
r_p_medlim	-.0288071	.0424191	-0.68	0.497	-.1119469	.0543327
r_p_hsgrad	-.0771452	.030033	-2.57	0.010	-.1360089	-.0182816
r_p_had_job	.1755038	.0327174	5.36	0.000	.1113788	.2396288
r_p_prob_drugalc	.1994232	.0814511	2.45	0.014	.039782	.3590644
r_p_prob_mh	.0787933	.0318471	2.47	0.013	.0163741	.1412125
r_p_usvet	-.1003563	.1059947	-0.95	0.344	-.3081021	.1073894
r_p_iq	5.11e-06	.0010836	0.00	0.996	-.0021187	.0021289
r_18under_1arr	.1587143	.0343812	4.62	0.000	.0913285	.2261002
c_age	-.0025418	.0019648	-1.29	0.196	-.0063928	.0013092
c_black	-.0530746	.0401308	-1.32	0.186	-.1317295	.0255803
c_married	-.0281907	.0526119	-0.54	0.592	-.131308	.0749267
c_islam	-.0309163	.0462243	-0.67	0.504	-.1215144	.0596818
c_urban	-.0302396	.036849	-0.82	0.412	-.1024622	.0419831
c_maxsent	-.000288	.0001072	-2.69	0.007	-.0004981	-.0000778
c_cust_gt3	-.0223695	.0360898	-0.62	0.535	-.0931041	.0483651
c_misAB	.0205923	.0354201	0.58	0.561	-.0488297	.0900144
c_hadtc	-.002487	.0674149	-0.04	0.971	-.1346178	.1296437
c_ever_ac_sol	.0763478	.0489175	1.56	0.119	-.0195287	.1722243
c_3charge	-.0185221	.0291529	-0.64	0.525	-.0756608	.0386166
c_p_medlim	-.0634833	.0423249	-1.50	0.134	-.1464387	.019472
c_p_hsgrad	-.0586328	.0301146	-1.95	0.052	-.1176563	.0003906
c_p_had_job	-.0034543	.033636	-0.10	0.918	-.0693796	.062471
c_p_prob_drugalc	-.0589982	.0817804	-0.72	0.471	-.2192849	.1012885
c_p_prob_mh	-.0094601	.0311921	-0.30	0.762	-.0705956	.0516754
c_p_usvet	-.1069302	.1056971	-1.01	0.312	-.3140928	.1002324
c_p_iq	-.0013038	.0010163	-1.28	0.199	-.0032957	.000688
c_18under_1arr	.0445638	.0335912	1.33	0.185	-.0212738	.1104013
c_apv	.0054835	.0495135	0.11	0.912	-.0915613	.1025282
cp_age	-.0056994	.0037145	-1.53	0.125	-.0129796	.0015808
cp_black	-.0368222	.0714925	-0.52	0.607	-.1769449	.1033004
cp_married	.0378725	.083037	0.46	0.648	-.124877	.200622
cp_islam	.0923088	.0873748	1.06	0.291	-.0789428	.2635603
cp_urban	-.0310252	.0693786	-0.45	0.655	-.1670047	.1049543
cp_maxsent	.0003632	.0002222	1.63	0.102	-.0000723	.0007987
cp_pri_narr	.0025465	.0057995	0.44	0.661	-.0088203	.0139133
cp_cust_gt3	.0667208	.0668081	1.00	0.318	-.0642207	.1976623
cp_misAB	-.0819538	.0699554	-1.17	0.241	-.2190638	.0551561
cp_hadtc	-.0091465	.1361161	-0.07	0.946	-.2759291	.2576362
cp_hasPriorI	-.0979706	.0868805	-1.13	0.259	-.2682533	.072312
cp_ever_ac_sol	.1044507	.078892	1.32	0.186	-.0501748	.2590763

```
        cp_3charge |   .0256027   .0591407     0.43   0.665    -.0903109    .1415164
        cp_p_medlim |  -.1015944   .0700434    -1.45   0.147    -.2388769     .035688
        cp_p_hsgrad |   .0186906   .0608153     0.31   0.759    -.1005052    .1378865
       cp_p_had_job |   -.179112   .0602089    -2.97   0.003    -.2971192   -.0611048
   cp_p_prob_drugalc |  -.0851818   .1023877    -0.83   0.405    -.2858581    .1154945
       cp_p_prob_mh |   .0314383   .0601988     0.52   0.602    -.0865492    .1494259
         cp_p_usvet |   .0867178    .119859     0.72   0.469    -.1482017    .3216372
            cp_p_iq |  -.0013519   .0019816    -0.68   0.495    -.0052357     .002532
     cp_18under_1arr |   .0517106    .067101     0.77   0.441    -.0798049     .183226
             cp_apv |   .1189585   .1025543     1.16   0.246    -.0820442    .3199611
        c_hasPriorI |   .0586822   .0412718     1.42   0.155     -.022209    .1395735
         r_pri_narr |   .0813271   .0046384    17.53   0.000     .0722361    .0904181
       rel_pri_narr |   .0030515   .0028408     1.07   0.283    -.0025163    .0086192
          stretches |  -.0156401   .0177839    -0.88   0.379    -.0504958    .0192157
         r_time2rel |  -.0000152   .0000602    -0.25   0.800    -.0001333    .0001028
         r_staytime |  -.0000388   .0000731    -0.53   0.595    -.0001821    .0001045
           same_age |  -.0071182   .0308371    -0.23   0.817    -.0675579    .0533215
          same_race |   .0289203    .034093     0.85   0.396    -.0379007    .0957413
       same_married |   -.009236   .0519484    -0.18   0.859    -.1110529     .092581
         same_islam |   -.067044   .0445977    -1.50   0.133    -.1544538    .0203658
         same_urban |    .095726   .0354229     2.70   0.007     .0262985    .1651536
      same_cust_gt3 |  -.0301476   .0348707    -0.86   0.387     -.098493    .0381978
         same_misAB |   .0304254   .0329205     0.92   0.355    -.0340976    .0949484
         same_hadtc |   .0140369     .06726     0.21   0.835    -.1177902    .1458641
    same_ever_ac_sol |   .0426113   .0474099     0.90   0.369    -.0503105    .1355331
       same_3charge |  -.0306123   .0282145    -1.08   0.278    -.0859117    .0246871
      same_p_medlim |   .0006757   .0415361     0.02   0.987    -.0807336    .0820851
      same_p_hsgrad |  -.0031001   .0280471    -0.11   0.912    -.0580713    .0518711
     same_p_had_job |  -.0875164   .0326408    -2.68   0.007    -.1514911   -.0235417
 same_p_prob_drugalc |   .0480897   .0808734     0.59   0.552    -.1104194    .2065987
     same_p_prob_mh |  -.0740446   .0299974    -2.47   0.014    -.1328384   -.0152508
       same_p_usvet |  -.0974246   .1040849    -0.94   0.349    -.3014273    .1065782
          same_p_iq |  -.0096986   .0273357    -0.35   0.723    -.0632755    .0438784
   same_18under_1arr |   .0120066   .0299944     0.40   0.689    -.0467814    .0707945
              _cons |   1.189355   .3540878     3.36   0.001     .4953557    1.883355
-------------------+----------------------------------------------------------------
            /athrho |  -.0658155   .0415398    -1.58   0.113    -.1472319    .0156009
           /lnsigma |   4.683968   .0070253   666.73   0.000     4.670198    4.697737
-------------------+----------------------------------------------------------------
                rho |  -.0657206   .0413603                      -.1461772    .0155997
              sigma |   108.1985   .7601226                       106.7189    109.6986
------------------------------------------------------------------------------------
Instrumented:  total_tt
Instruments:   r_age r_black r_married r_islam r_urban r_maxsent r_cust_gt3 r_misAB
               r_hadtc r_ever_ac_sol r_3charge r_p_medlim r_p_hsgrad r_p_had_job
               r_p_prob_drugalc r_p_prob_mh r_p_usvet r_p_iq r_18under_1arr c_age
               c_black c_married c_islam c_urban c_maxsent c_cust_gt3 c_misAB
               c_hadtc c_ever_ac_sol c_3charge c_p_medlim c_p_hsgrad c_p_had_job
               c_p_prob_drugalc c_p_prob_mh c_p_usvet c_p_iq c_18under_1arr c_apv
               cp_age cp_black cp_married cp_islam cp_urban cp_maxsent cp_pri_narr
               cp_cust_gt3 cp_misAB cp_hadtc cp_hasPriorI cp_ever_ac_sol cp_3charge
               cp_p_medlim cp_p_hsgrad cp_p_had_job cp_p_prob_drugalc cp_p_prob_mh
               cp_p_usvet cp_p_iq cp_18under_1arr cp_apv c_hasPriorI r_pri_narr
               rel_pri_narr stretches r_time2rel r_staytime same_age same_race
               same_married same_islam same_urban same_cust_gt3 same_misAB
               same_hadtc same_ever_ac_sol same_3charge same_p_medlim same_p_hsgrad
               same_p_had_job same_p_prob_drugalc same_p_prob_mh same_p_usvet
               same_p_iq same_18under_1arr cellsqft_tt_fa tier_tt_fa c_time2r_tt
               52.fac_tt 54.fac_tt 55.fac_tt 56.fac_tt 57.fac_tt 58.fac_tt
               59.fac_tt 60.fac_tt 61.fac_tt 62.fac_tt 63.fac_tt 64.fac_tt
               65.fac_tt 66.fac_tt 68.fac_tt 69.fac_tt 72.fac_tt 73.fac_tt
               75.fac_tt 76.fac_tt 77.fac_tt 78.fac_tt 81.fac_tt 82.fac_tt
------------------------------------------------------------------------------------
Wald test of exogeneity (/athrho = 0): chi2(1) =     2.51 Prob > chi2 = 0.1131
```

Outcome model #1. Four-year recidivism outcomes. *ivprobit*.

```
Probit model with endogenous regressors          Number of obs   =      10131
                                                 Wald chi2(86)   =    1713.47
Log likelihood = -67521.998                      Prob > chi2     =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
total_tt	.0007904	.0003597	2.20	0.028	.0000854	.0014954
r_age	-.0307855	.0019181	-16.05	0.000	-.0345449	-.0270261
r_black	.1481954	.0505447	2.93	0.003	.0491295	.2472612
r_married	-.1230124	.051352	-2.40	0.017	-.2236605	-.0223643
r_islam	.2477032	.0504312	4.91	0.000	.1488598	.3465466
r_urban	-.0806279	.0370702	-2.18	0.030	-.1532842	-.0079716
r_maxsent	-.0003848	.0004975	-0.77	0.439	-.0013599	.0005903
r_cust_gt3	.1515098	.0393349	3.85	0.000	.0744148	.2286048
r_misAB	.0682244	.0405089	1.68	0.092	-.0111716	.1476204
r_hadtc	.126828	.082896	1.53	0.126	-.0356452	.2893012
r_ever_ac_sol	.0197665	.0528441	0.37	0.708	-.0838061	.1233391
r_3charge	.0405349	.0291386	1.39	0.164	-.0165757	.0976454
r_p_medlim	-.0039324	.0421045	-0.09	0.926	-.0864558	.0785909
r_p_hsgrad	-.1028035	.0306295	-3.36	0.001	-.1628362	-.0427709
r_p_had_job	-.0325458	.0330055	-0.99	0.324	-.0972354	.0321437
r_p_prob_drugalc	.2772089	.0796937	3.48	0.001	.1210121	.4334058
r_p_prob_mh	.2111625	.0321872	6.56	0.000	.1480768	.2742482
r_p_usvet	-.0304442	.0963446	-0.32	0.752	-.2192761	.1583877
r_p_iq	-.0000263	.00109	-0.02	0.981	-.0021627	.0021101
r_18under_1arr	.1006012	.0356408	2.82	0.005	.0307465	.1704558
c_age	-.0041765	.00194	-2.15	0.031	-.0079788	-.0003742
c_black	-.0015725	.0407502	-0.04	0.969	-.0814414	.0782964
c_married	-.0497494	.0511742	-0.97	0.331	-.1500491	.0505502
c_islam	-.1051863	.0488227	-2.15	0.031	-.200877	-.0094957
c_urban	-.0268648	.0369666	-0.73	0.467	-.099318	.0455884
c_maxsent	-.0002027	.0001048	-1.93	0.053	-.0004081	2.68e-06
c_cust_gt3	-.0376494	.0377066	-1.00	0.318	-.111553	.0362543
c_misAB	.0175736	.0362731	0.48	0.628	-.0535203	.0886676
c_hadtc	-.0832445	.0680748	-1.22	0.221	-.2166686	.0501797
c_ever_ac_sol	.0974313	.0503334	1.94	0.053	-.0012204	.196083
c_3charge	.0061504	.0294293	0.21	0.834	-.05153	.0638308
c_p_medlim	-.0240044	.0419571	-0.57	0.567	-.1062388	.05823
c_p_hsgrad	-.040184	.0306692	-1.31	0.190	-.1002945	.0199266
c_p_had_job	.0041293	.0338995	0.12	0.903	-.0623124	.070571
c_p_prob_drugalc	.0730353	.0799516	0.91	0.361	-.083667	.2297375
c_p_prob_mh	-.0050011	.031567	-0.16	0.874	-.0668713	.0568691
c_p_usvet	.0064768	.0959106	0.07	0.946	-.1815044	.1944581
c_p_iq	-.0017267	.0010227	-1.69	0.091	-.0037312	.0002778
c_18under_1arr	.0402296	.0347472	1.16	0.247	-.0278736	.1083328
c_apv	.0303633	.0504478	0.60	0.547	-.0685127	.1292392
cp_age	-.0060089	.0036814	-1.63	0.103	-.0132243	.0012065
cp_black	-.0344554	.0718799	-0.48	0.632	-.1753375	.1064267
cp_married	-.0720046	.082415	-0.87	0.382	-.233535	.0895259
cp_islam	.0246787	.0892951	0.28	0.782	-.1503365	.1996939
cp_urban	-.0793427	.0692825	-1.15	0.252	-.2151339	.0564486
cp_maxsent	.0002511	.000224	1.12	0.262	-.0001879	.00069
cp_pri_narr	.0051886	.0058178	0.89	0.372	-.0062142	.0165913
cp_cust_gt3	.167084	.0685289	2.44	0.015	.0327699	.3013981
cp_misAB	-.0649268	.0705689	-0.92	0.358	-.2032393	.0733857
cp_hadtc	-.1196683	.1351782	-0.89	0.376	-.3846127	.1452761
cp_hasPriorI	-.0887449	.087152	-1.02	0.309	-.2595596	.0820698
cp_ever_ac_sol	.0714611	.079551	0.90	0.369	-.0844561	.2273783
cp_3charge	.1289025	.0591531	2.18	0.029	.0129645	.2448405
cp_p_medlim	-.0687115	.0699417	-0.98	0.326	-.2057948	.0683718
cp_p_hsgrad	.0362248	.0611959	0.59	0.554	-.083717	.1561667
cp_p_had_job	-.0809748	.0603181	-1.34	0.179	-.1991961	.0372464
cp_p_prob_drugalc	-.0490926	.1020454	-0.48	0.630	-.249098	.1509128
cp_p_prob_mh	-.0264218	.0602706	-0.44	0.661	-.14455	.0917064
cp_p_usvet	.069122	.1178022	0.59	0.557	-.161766	.3000101
cp_p_iq	-.0027808	.0019676	-1.41	0.158	-.0066373	.0010758
cp_18under_1arr	.0526302	.067773	0.78	0.437	-.0802024	.1854628
cp_apv	.0949527	.1031826	0.92	0.357	-.1072815	.2971869
c_hasPriorI	.0516813	.0418229	1.24	0.217	-.0302902	.1336528
r_pri_narr	.0790517	.0047594	16.61	0.000	.0697234	.08838
rel_pri_narr	.00364	.0028659	1.27	0.204	-.0019771	.0092572
stretches	-.0367245	.0178992	-2.05	0.040	-.0718062	-.0016427
r_time2rel	-.0001015	.0000599	-1.69	0.090	-.0002189	.0000159
r_staytime	-.0002268	.0000725	-3.13	0.002	-.000369	-.0000846

```
           same_age |  -.0110282   .0306603    -0.36   0.719    -.0711212    .0490647
          same_race |  -.0072257   .0343969    -0.21   0.834    -.0746423    .0601909
       same_married |  -.0430607   .0505037    -0.85   0.394    -.1420462    .0559248
         same_islam |  -.1315512   .0470876    -2.79   0.005    -.2238413   -.0392612
         same_urban |   .0374028   .0355838     1.05   0.293    -.0323402    .1071458
      same_cust_gt3 |  -.0204359   .0364852    -0.56   0.575    -.0919455    .0510738
         same_misAB |   .0200218   .0337412     0.59   0.553    -.0461097    .0861534
         same_hadtc |   .0006718   .0679417     0.01   0.992    -.1324916    .1338351
    same_ever_ac_sol |      .0473   .0488227     0.97   0.333    -.0483907    .1429908
        same_3charge |  -.0229627   .0284975    -0.81   0.420    -.0788167    .0328913
       same_p_medlim |   .0091662   .0411102     0.22   0.824    -.0714083    .0897406
       same_p_hsgrad |   .0161039   .0285711     0.56   0.573    -.0398944    .0721022
      same_p_had_job |    -.07022   .0328944    -2.13   0.033    -.1346918   -.0057482
 same_p_prob_drugalc |  -.0451696   .0791021    -0.57   0.568    -.2002069    .1098677
      same_p_prob_mh |  -.0463193   .0303938    -1.52   0.128    -.1058901    .0132516
       same_p_usvet |    .001206   .0942478     0.01   0.990    -.1835164    .1859283
          same_p_iq |  -.0082592   .0276356    -0.30   0.765    -.0624239    .0459055
   same_18under_1arr |   .0119507   .0312279     0.38   0.702    -.0492548    .0731562
              _cons |   1.548824   .3509844     4.41   0.000     .8609076    2.236741
--------------------+----------------------------------------------------------------
            /athrho |  -.1223623   .0418448    -2.92   0.003    -.2043767    -.040348
           /lnsigma |   4.683977   .0070254   666.72   0.000     4.670208    4.697747
--------------------+----------------------------------------------------------------
                rho |  -.1217553   .0412245                     -.2015778   -.0403261
              sigma |   108.1995   .7601445                      106.7199    109.6997
-------------------------------------------------------------------------------------
Instrumented:  total_tt
Instruments:   r_age r_black r_married r_islam r_urban r_maxsent r_cust_gt3 r_misAB
               r_hadtc r_ever_ac_sol r_3charge r_p_medlim r_p_hsgrad r_p_had_job
               r_p_prob_drugalc r_p_prob_mh r_p_usvet r_p_iq r_18under_1arr c_age
               c_black c_married c_islam c_urban c_maxsent c_cust_gt3 c_misAB
               c_hadtc c_ever_ac_sol c_3charge c_p_medlim c_p_hsgrad c_p_had_job
               c_p_prob_drugalc c_p_prob_mh c_p_usvet c_p_iq c_18under_1arr c_apv
               cp_age cp_black cp_married cp_islam cp_urban cp_maxsent cp_pri_narr
               cp_cust_gt3 cp_misAB cp_hadtc cp_hasPriorI cp_ever_ac_sol cp_3charge
               cp_p_medlim cp_p_hsgrad cp_p_had_job cp_p_prob_drugalc cp_p_prob_mh
               cp_p_usvet cp_p_iq cp_18under_1arr cp_apv c_hasPriorI r_pri_narr
               rel_pri_narr stretches r_time2rel r_staytime same_age same_race
               same_married same_islam same_urban same_cust_gt3 same_misAB
               same_hadtc same_ever_ac_sol same_3charge same_p_medlim same_p_hsgrad
               same_p_had_job same_p_prob_drugalc same_p_prob_mh same_p_usvet
               same_p_iq same_18under_1arr cellsqft_tt_fa tier_tt_fa c_time2r_tt
               52.fac_tt 54.fac_tt 55.fac_tt 56.fac_tt 57.fac_tt 58.fac_tt
               59.fac_tt 60.fac_tt 61.fac_tt 62.fac_tt 63.fac_tt 64.fac_tt
               65.fac_tt 66.fac_tt 68.fac_tt 69.fac_tt 72.fac_tt 73.fac_tt
               75.fac_tt 76.fac_tt 77.fac_tt 78.fac_tt 81.fac_tt 82.fac_tt
-------------------------------------------------------------------------------------
Wald test of exogeneity (/athrho = 0): chi2(1) =     8.55 Prob > chi2 = 0.0035
```

Outcome model #2. Four-year rearrest outcomes. *ivprobit*.

```
Probit model with endogenous regressors          Number of obs   =      10131
                                                 Wald chi2(89)   =    1943.10
Log likelihood = -67676.281                      Prob > chi2     =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
total_tt	.0002101	.0003597	0.58	0.559	-.0004948	.000915
r_age	-.0224667	.0023421	-9.59	0.000	-.0270572	-.0178763
r_black	.1958316	.0499621	3.92	0.000	.0979078	.2937555
r_married	-.1207451	.052888	-2.28	0.022	-.2244036	-.0170865
r_islam	.236757	.0480082	4.93	0.000	.1426626	.3308513
r_urban	.0379813	.0370212	1.03	0.305	-.034579	.1105415
r_maxsent	-.0043909	.0005022	-8.74	0.000	-.0053752	-.0034065
r_cust_gt3	.1145042	.0376605	3.04	0.002	.0406911	.1883174
r_misAB	-.0865226	.0464947	-1.86	0.063	-.1776505	.0046053
r_hadtc	.0106119	.0824081	0.13	0.898	-.150905	.1721288
r_ever_ac_sol	.0135476	.0517245	0.26	0.793	-.0878305	.1149256
r_3charge	.0550036	.0289056	1.90	0.057	-.0016504	.1116575
r_p_medlim	-.0301387	.0424716	-0.71	0.478	-.1133815	.0531041
r_p_hsgrad	-.2485598	.0385053	-6.46	0.000	-.3240288	-.1730909
r_p_had_job	.1788296	.0327968	5.45	0.000	.114549	.2431102
r_p_prob_drugalc	.0054087	.0861243	0.06	0.950	-.1633918	.1742092
r_p_prob_mh	.0795282	.0319224	2.49	0.013	.0169615	.1420949
r_p_usvet	-.110376	.1059639	-1.04	0.298	-.3180613	.0973094
r_p_iq	.0002512	.0010865	0.23	0.817	-.0018782	.0023806
r_18under_1arr	-.062268	.0462804	-1.35	0.178	-.1529759	.0284399
c_age	-.003362	.0022619	-1.49	0.137	-.0077954	.0010713
c_black	-.0517519	.0402177	-1.29	0.198	-.1305772	.0270734
c_married	-.0228063	.0527315	-0.43	0.665	-.1261581	.0805455
c_islam	-.0313321	.0463766	-0.68	0.499	-.1222286	.0595644
c_urban	-.0237972	.0369554	-0.64	0.520	-.0962284	.0486341
c_maxsent	-.0002856	.0001077	-2.65	0.008	-.0004966	-.0000746
c_cust_gt3	-.0280404	.036186	-0.77	0.438	-.0989637	.0428829
c_misAB	.0385013	.0418011	0.92	0.357	-.0434274	.12043
c_hadtc	-.0031951	.0675616	-0.05	0.962	-.1356134	.1292232
c_ever_ac_sol	.0732789	.0490305	1.49	0.135	-.022819	.1693768
c_3charge	-.0164919	.0292191	-0.56	0.572	-.0737604	.0407765
c_p_medlim	-.0641817	.0423729	-1.51	0.130	-.147231	.0188676
c_p_hsgrad	-.046836	.0373437	-1.25	0.210	-.1200283	.0263563
c_p_had_job	-.0047048	.033706	-0.14	0.889	-.0707673	.0613577
c_p_prob_drugalc	-.0450841	.0857519	-0.53	0.599	-.2131548	.1229866
c_p_prob_mh	-.0070257	.0312519	-0.22	0.822	-.0682783	.0542269
c_p_usvet	-.1134725	.1056693	-1.07	0.283	-.3205806	.0936356
c_p_iq	-.0012408	.0010173	-1.22	0.223	-.0032346	.0007531
c_18under_1arr	.0615879	.0435617	1.41	0.157	-.0237915	.1469672
c_apv	.0230802	.0538131	0.43	0.668	-.0823916	.1285521
cp_age	-.0052663	.0044037	-1.20	0.232	-.0138974	.0033648
cp_black	-.0312571	.0717342	-0.44	0.663	-.1718536	.1093394
cp_married	.0434525	.0832193	0.52	0.602	-.1196543	.2065593
cp_islam	.091819	.0876615	1.05	0.295	-.0799943	.2636324
cp_urban	-.0314833	.0695483	-0.45	0.651	-.1677954	.1048288
cp_maxsent	.0003801	.0002228	1.71	0.088	-.0000566	.0008168
cp_pri_narr	.0010508	.0071199	0.15	0.883	-.012904	.0150056
cp_cust_gt3	.0549868	.0671606	0.82	0.413	-.0766455	.1866191
cp_misAB	-.0905393	.0842917	-1.07	0.283	-.2557479	.0746694
cp_hadtc	-.0054347	.1363872	-0.04	0.968	-.2727487	.2618793
cp_hasPriorI	-.0999923	.0871632	-1.15	0.251	-.2708289	.0708444
cp_ever_ac_sol	.1111663	.0790757	1.41	0.160	-.0438192	.2661517
cp_3charge	.0267865	.0592678	0.45	0.651	-.0893763	.1429493
cp_rsth	.0126162	.0454527	0.28	0.781	-.0764695	.1017019
cp_p_medlim	-.1001068	.0701952	-1.43	0.154	-.2376868	.0374732
cp_p_hsgrad	.005417	.0768474	0.07	0.944	-.1452011	.1560351
cp_p_had_job	-.1803526	.0603729	-2.99	0.003	-.2986814	-.0620238
cp_p_prob_drugalc	-.0829424	.1154754	-0.72	0.473	-.3092701	.1433853
cp_p_prob_mh	.0301433	.0603438	0.50	0.617	-.0881283	.1484149
cp_p_usvet	.082681	.1201926	0.69	0.492	-.1528922	.3182542
cp_p_iq	-.0013999	.0019887	-0.70	0.481	-.0052977	.0024979
cp_18under_1arr	.0311114	.0892622	0.35	0.727	-.1438393	.2060621
cp_apv	.0996639	.1112661	0.90	0.370	-.1184136	.3177414
c_hasPriorI	.0623706	.0413843	1.51	0.132	-.018741	.1434823
r_pri_narr	.0583749	.0060418	9.66	0.000	.0465331	.0702166
rel_pri_narr	.0039674	.0034451	1.15	0.249	-.0027848	.0107197
r_rsth	.1537731	.0320869	4.79	0.000	.090884	.2166622
rel_rsth	-.016252	.0216617	-0.75	0.453	-.0587081	.0262041

```
         stretches |  -.0119957   .0177793    -0.67   0.500    -.0468425    .0228511
        r_time2rel |  -.0000157   .0000605    -0.26   0.795    -.0001342    .0001028
        r_staytime |  -.0000248   .0000733    -0.34   0.735    -.0001684    .0001188
          same_age |  -.0033959   .0308963    -0.11   0.912    -.0639516    .0571598
         same_race |   .0267913   .0342075     0.78   0.434    -.0402541    .0938367
      same_married |  -.0053451   .0520683    -0.10   0.918    -.1073971     .096707
        same_islam |  -.0705263   .0447466    -1.58   0.115    -.1582281    .0171755
        same_urban |   .1000209   .0355085     2.82   0.005     .0304256    .1696162
     same_cust_gt3 |  -.0292674   .0349242    -0.84   0.402    -.0977176    .0391829
        same_misAB |   .0320487   .0330042     0.97   0.332    -.0326384    .0967358
        same_hadtc |   .0162255    .067355     0.24   0.810     -.115788    .1482389
  same_ever_ac_sol |   .0415952   .0475132     0.88   0.381    -.0515289    .1347193
      same_3charge |  -.0295342   .0282854    -1.04   0.296    -.0849726    .0259043
     same_p_medlim |   .0011465   .0415788     0.03   0.978    -.0803464    .0826394
     same_p_hsgrad |   .0004327    .028123     0.02   0.988    -.0546873    .0555528
    same_p_had_job |  -.0866099   .0327151    -2.65   0.008    -.1507303   -.0224895
same_p_prob_drugalc |   .0575429    .081311     0.71   0.479    -.1018238    .2169096
    same_p_prob_mh |  -.0724955   .0300557    -2.41   0.016    -.1314035   -.0135875
      same_p_usvet |  -.1029441   .1040483    -0.99   0.322    -.3068751    .1009869
         same_p_iq |  -.0104422   .0274005    -0.38   0.703    -.0641463    .0432619
  same_18under_1arr |   .0103129   .0300525     0.34   0.731    -.0485889    .0692148
             _cons |   .6598748   .3943986     1.67   0.094    -.1131322    1.432882
-------------------+----------------------------------------------------------------
           /athrho |  -.0518627   .0414161    -1.25   0.210    -.1330368    .0293115
          /lnsigma |   4.682745   .0070252   666.56   0.000     4.668975    4.696514
-------------------+----------------------------------------------------------------
               rho |  -.0518162    .041305                     -.1322575    .0293031
             sigma |   108.0663   .7591913                      106.5885    109.5645
------------------------------------------------------------------------------------
Instrumented:  total_tt
Instruments:   r_age r_black r_married r_islam r_urban r_maxsent r_cust_gt3 r_misAB
               r_hadtc r_ever_ac_sol r_3charge r_p_medlim r_p_hsgrad r_p_had_job
               r_p_prob_drugalc r_p_prob_mh r_p_usvet r_p_iq r_18under_1arr c_age
               c_black c_married c_islam c_urban c_maxsent c_cust_gt3 c_misAB
               c_hadtc c_ever_ac_sol c_3charge c_p_medlim c_p_hsgrad c_p_had_job
               c_p_prob_drugalc c_p_prob_mh c_p_usvet c_p_iq c_18under_1arr c_apv
               cp_age cp_black cp_married cp_islam cp_urban cp_maxsent cp_pri_narr
               cp_cust_gt3 cp_misAB cp_hadtc cp_hasPriorI cp_ever_ac_sol cp_3charge
               cp_rsth cp_p_medlim cp_p_hsgrad cp_p_had_job cp_p_prob_drugalc
               cp_p_prob_mh cp_p_usvet cp_p_iq cp_18under_1arr cp_apv c_hasPriorI
               r_pri_narr rel_pri_narr r_rsth rel_rsth stretches r_time2rel
               r_staytime same_age same_race same_married same_islam same_urban
               same_cust_gt3 same_misAB same_hadtc same_ever_ac_sol same_3charge
               same_p_medlim same_p_hsgrad same_p_had_job same_p_prob_drugalc
               same_p_prob_mh same_p_usvet same_p_iq same_18under_1arr
               cellsqft_tt_fa tier_tt_fa c_time2r_tt 52.fac_tt 54.fac_tt 55.fac_tt
               56.fac_tt 57.fac_tt 58.fac_tt 59.fac_tt 60.fac_tt 61.fac_tt
               62.fac_tt 63.fac_tt 64.fac_tt 65.fac_tt 66.fac_tt 68.fac_tt
               69.fac_tt 72.fac_tt 73.fac_tt 75.fac_tt 76.fac_tt 77.fac_tt
               78.fac_tt 81.fac_tt 82.fac_tt
------------------------------------------------------------------------------------
Wald test of exogeneity (/athrho = 0): chi2(1) =     1.57 Prob > chi2 = 0.2105
```

Outcome model #2. Four-year recidivism outcomes. *ivprobit*.

Probit model with endogenous regressors		Number of obs =	10131
		Wald chi2(89) =	1760.62
Log likelihood =	-67484.39	Prob > chi2 =	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
total_tt	.0006775	.0003598	1.88	0.060	-.0000277	.0013827
r_age	-.0214696	.0022983	-9.34	0.000	-.0259741	-.0169651
r_black	.1485371	.0507091	2.93	0.003	.049149	.2479252
r_married	-.1137221	.0514905	-2.21	0.027	-.2146416	-.0128027
r_islam	.2374519	.0506286	4.69	0.000	.1382217	.3366821
r_urban	-.0879995	.0371938	-2.37	0.018	-.160898	-.015101
r_maxsent	-.0003185	.0004995	-0.64	0.524	-.0012976	.0006606
r_cust_gt3	.1460683	.039432	3.70	0.000	.068783	.2233536
r_misAB	-.1106916	.0474311	-2.33	0.020	-.2036549	-.0177283
r_hadtc	.1235419	.0831561	1.49	0.137	-.039441	.2865248
r_ever_ac_sol	.0200456	.0530035	0.38	0.705	-.0838392	.1239305
r_3charge	.0427524	.0292256	1.46	0.144	-.0145288	.1000336
r_p_medlim	-.0055949	.0421775	-0.13	0.894	-.0882613	.0770715
r_p_hsgrad	-.2805575	.0392423	-7.15	0.000	-.3574711	-.203644
r_p_had_job	-.030282	.0330811	-0.92	0.360	-.0951196	.0345557
r_p_prob_drugalc	.077178	.0845548	0.91	0.361	-.0885464	.2429024
r_p_prob_mh	.2130341	.0322815	6.60	0.000	.1497636	.2763046
r_p_usvet	-.0415102	.0963486	-0.43	0.667	-.2303499	.1473295
r_p_iq	.0002192	.0010934	0.20	0.841	-.0019239	.0023623
r_18under_1arr	-.1290409	.0476203	-2.71	0.007	-.2223749	-.0357069
c_age	-.0036564	.0022449	-1.63	0.103	-.0080564	.0007435
c_black	-.0005727	.0408568	-0.01	0.989	-.0806506	.0795052
c_married	-.0434759	.0512945	-0.85	0.397	-.1440113	.0570595
c_islam	-.1074673	.0490076	-2.19	0.028	-.2035204	-.0114143
c_urban	-.0223118	.0370871	-0.60	0.547	-.0950012	.0503777
c_maxsent	-.0001978	.0001054	-1.88	0.061	-.0004044	8.79e-06
c_cust_gt3	-.0453361	.037821	-1.20	0.231	-.1194638	.0287917
c_misAB	.008939	.0426985	0.21	0.834	-.0747485	.0926265
c_hadtc	-.087133	.0682882	-1.28	0.202	-.2209755	.0467095
c_ever_ac_sol	.0938221	.050497	1.86	0.063	-.0051503	.1927945
c_3charge	.0083962	.0295095	0.28	0.776	-.0494414	.0662338
c_p_medlim	-.0241629	.0420207	-0.58	0.565	-.106522	.0581962
c_p_hsgrad	-.0544717	.0378602	-1.44	0.150	-.1286763	.0197329
c_p_had_job	.0023101	.0339776	0.07	0.946	-.0642847	.0689049
c_p_prob_drugalc	.0565269	.0840546	0.67	0.501	-.1082171	.2212709
c_p_prob_mh	-.0036727	.0316318	-0.12	0.908	-.0656698	.0583244
c_p_usvet	.0008461	.0958947	0.01	0.993	-.1871041	.1887963
c_p_iq	-.0016703	.0010234	-1.63	0.103	-.0036762	.0003355
c_18under_1arr	.0228641	.0446809	0.51	0.609	-.0647089	.110437
c_apv	.0241093	.0547744	0.44	0.660	-.0832466	.1314653
cp_age	-.0057687	.0043747	-1.32	0.187	-.014343	.0028056
cp_black	-.0297001	.0721422	-0.41	0.681	-.1710961	.1116959
cp_married	-.0682745	.0826572	-0.83	0.409	-.2302797	.0937306
cp_islam	.0241312	.0896178	0.27	0.788	-.1515165	.1997788
cp_urban	-.080423	.0694748	-1.16	0.247	-.2165911	.0557452
cp_maxsent	.0002681	.0002249	1.19	0.233	-.0001727	.0007089
cp_pri_narr	.0039319	.0071395	0.55	0.582	-.0100613	.017925
cp_cust_gt3	.1588338	.0689146	2.30	0.021	.0237637	.293904
cp_misAB	-.0709264	.0846461	-0.84	0.402	-.2368297	.0949768
cp_hadtc	-.1206	.1355667	-0.89	0.374	-.3863058	.1451059
cp_hasPriorI	-.0904964	.087426	-1.04	0.301	-.2618483	.0808554
cp_ever_ac_sol	.078129	.0797869	0.98	0.327	-.0782505	.2345085
cp_3charge	.1314222	.0592978	2.22	0.027	.0152007	.2476437
cp_rsth	.0104192	.0455111	0.23	0.819	-.078781	.0996193
cp_p_medlim	-.0694849	.0700994	-0.99	0.322	-.2068772	.0679074
cp_p_hsgrad	.0252524	.0769993	0.33	0.743	-.1256633	.1761682
cp_p_had_job	-.0809561	.0604909	-1.34	0.181	-.1995161	.0376038
cp_p_prob_drugalc	-.0447594	.1153124	-0.39	0.698	-.2707675	.1812487
cp_p_prob_mh	-.0281065	.0604292	-0.47	0.642	-.1465455	.0903325
cp_p_usvet	.0666785	.1180993	0.56	0.572	-.164792	.2981489
cp_p_iq	-.0028491	.0019743	-1.44	0.149	-.0067187	.0010205
cp_18under_1arr	.033833	.0899568	0.38	0.707	-.142479	.210145
cp_apv	.0763648	.1118543	0.68	0.495	-.1428655	.2955951
c_hasPriorI	.053749	.0419593	1.28	0.200	-.0284896	.1359876
r_pri_narr	.0516552	.0062326	8.29	0.000	.0394394	.0638709
rel_pri_narr	.0021524	.0034753	0.62	0.536	-.0046591	.0089639
r_rsth	.186479	.0325005	5.74	0.000	.1227792	.2501787
rel_rsth	.0102181	.0218632	0.47	0.640	-.032633	.0530691

```
         stretches |  -.0329785   .0178986    -1.84   0.065    -.0680591    .0021021
        r_time2rel |  -.0001005   .0000602    -1.67   0.095    -.0002184    .0000174
        r_staytime |  -.0002156   .0000728    -2.96   0.003    -.0003583   -.0000729
          same_age |  -.0063396   .0307396    -0.21   0.837    -.0665881    .0539089
         same_race |  -.0100318   .0345241    -0.29   0.771    -.0776979    .0576342
      same_married |  -.0390961   .0506215    -0.77   0.440    -.1383125    .0601203
        same_islam |   -.136687    .047275    -2.89   0.004    -.2293443   -.0440298
        same_urban |    .042558   .0356833     1.19   0.233      -.02738    .1124959
     same_cust_gt3 |  -.0193833   .0365628    -0.53   0.596    -.0910451    .0522785
        same_misAB |   .0221568   .0338383     0.65   0.513    -.0441651    .0884786
        same_hadtc |   .0025078    .068108     0.04   0.971    -.1309814    .1359971
  same_ever_ac_sol |   .0463677   .0489745     0.95   0.344    -.0496205     .142356
      same_3charge |  -.0219662   .0285843    -0.77   0.442    -.0779903    .0340579
     same_p_medlim |   .0089411   .0411668     0.22   0.828    -.0717443    .0896265
     same_p_hsgrad |   .0203137    .028661     0.71   0.478    -.0358609    .0764882
    same_p_had_job |  -.0685502   .0329723    -2.08   0.038    -.1331746   -.0039258
same_p_prob_drugalc |  -.0374265   .0794677    -0.47   0.638    -.1931804    .1183274
    same_p_prob_mh |  -.0447692   .0304635    -1.47   0.142    -.1044765    .0149382
      same_p_usvet |  -.0037108   .0942353    -0.04   0.969    -.1884085     .180987
         same_p_iq |  -.0089685   .0277095    -0.32   0.746    -.0632783    .0453412
  same_18under_1arr |   .0103509   .0313094     0.33   0.741    -.0510144    .0717162
             _cons |   .9408018   .3921024     2.40   0.016     .1722951    1.709308
-------------------+----------------------------------------------------------------
           /athrho |  -.1079817   .0417273    -2.59   0.010    -.1897657   -.0261977
          /lnsigma |   4.682753   .0070254   666.55   0.000     4.668983    4.696522
-------------------+----------------------------------------------------------------
               rho |  -.1075639   .0412445                     -.1875201   -.0261917
             sigma |   108.0672   .7592105                      106.5893    109.5655
------------------------------------------------------------------------------------
Instrumented:  total_tt
Instruments:   r_age r_black r_married r_islam r_urban r_maxsent r_cust_gt3 r_misAB
               r_hadtc r_ever_ac_sol r_3charge r_p_medlim r_p_hsgrad r_p_had_job
               r_p_prob_drugalc r_p_prob_mh r_p_usvet r_p_iq r_18under_1arr c_age
               c_black c_married c_islam c_urban c_maxsent c_cust_gt3 c_misAB
               c_hadtc c_ever_ac_sol c_3charge c_p_medlim c_p_hsgrad c_p_had_job
               c_p_prob_drugalc c_p_prob_mh c_p_usvet c_p_iq c_18under_1arr c_apv
               cp_age cp_black cp_married cp_islam cp_urban cp_maxsent cp_pri_narr
               cp_cust_gt3 cp_misAB cp_hadtc cp_hasPriorI cp_ever_ac_sol cp_3charge
               cp_rsth cp_p_medlim cp_p_hsgrad cp_p_had_job cp_p_prob_drugalc
               cp_p_prob_mh cp_p_usvet cp_p_iq cp_18under_1arr cp_apv c_hasPriorI
               r_pri_narr rel_pri_narr r_rsth rel_rsth stretches r_time2rel
               r_staytime same_age same_race same_married same_islam same_urban
               same_cust_gt3 same_misAB same_hadtc same_ever_ac_sol same_3charge
               same_p_medlim same_p_hsgrad same_p_had_job same_p_prob_drugalc
               same_p_prob_mh same_p_usvet same_p_iq same_18under_1arr
               cellsqft_tt_fa tier_tt_fa c_time2r_tt 52.fac_tt 54.fac_tt 55.fac_tt
               56.fac_tt 57.fac_tt 58.fac_tt 59.fac_tt 60.fac_tt 61.fac_tt
               62.fac_tt 63.fac_tt 64.fac_tt 65.fac_tt 66.fac_tt 68.fac_tt
               69.fac_tt 72.fac_tt 73.fac_tt 75.fac_tt 76.fac_tt 77.fac_tt
               78.fac_tt 81.fac_tt 82.fac_tt
------------------------------------------------------------------------------------
Wald test of exogeneity (/athrho = 0): chi2(1) =     6.70 Prob > chi2 = 0.0097
```

Table 10. Two-stage least squares threshold models for rearrest and any reoffending, p-values and coefficients reported.

			Outcome Model #1				Outcome Model #2			
			Rearrest		Recidivism		Rearrest		Recidivism	
Days	n=1	n=0	Coef	p	Coef	p	Coef	p	Coef	p
30	9,914	217	0.0530	0.740	0.2119	0.180	0.0134	0.933	0.1683	0.285
60	8,636	1,495	0.0152	0.605	0.0606	0.038	0.0060	0.837	0.0504	0.082
90	7,219	2,912	0.0122	0.596	0.0505	0.027	0.0045	0.843	0.0420	0.065
120	5,966	4,165	0.0170	0.502	0.0597	0.017	0.0084	0.738	0.0502	0.044
150	4,920	5,211	0.0265	0.390	0.0733	0.016	0.0154	0.617	0.0610	0.045
180	3,981	6,150	0.0311	0.401	0.0825	0.024	0.0173	0.638	0.0674	0.064
210	3,131	7,000	0.0382	0.391	0.0951	0.031	0.0220	0.619	0.0776	0.077
240	2,489	7,642	0.0416	0.426	0.0977	0.059	0.0219	0.672	0.0765	0.136
270	1,951	8,180	0.0514	0.430	0.1120	0.083	0.0272	0.673	0.0865	0.176
300	1,531	8,600	0.0294	0.676	0.0886	0.203	0.0061	0.930	0.0645	0.349
330	1,226	8,905	0.0601	0.494	0.1413	0.105	0.0320	0.714	0.1127	0.191
360	961	9,170	0.1068	0.304	0.1666	0.105	0.0745	0.470	0.1343	0.187
390	776	9,355	0.1121	0.314	0.1608	0.147	0.0798	0.470	0.1295	0.239
420	647	9,484	0.1259	0.340	0.1865	0.156	0.0888	0.499	0.1499	0.251
450	513	9,618	0.1797	0.252	0.2402	0.125	0.1372	0.379	0.1976	0.203
480	419	9,712	0.1921	0.267	0.2068	0.230	0.1544	0.370	0.1704	0.320
510	350	9,781	0.1981	0.302	0.2198	0.251	0.1596	0.404	0.1826	0.339
540	282	9,849	0.1573	0.460	0.1732	0.415	0.1156	0.586	0.1339	0.526
570	239	9,892	0.1346	0.587	0.2188	0.378	0.0723	0.769	0.1604	0.515
600	192	9,939	0.1378	0.604	0.2220	0.401	0.0797	0.763	0.1660	0.527
630	156	9,975	0.2737	0.380	0.3237	0.298	0.1864	0.546	0.2401	0.435
660	134	9,997	0.1106	0.746	0.2114	0.535	0.0081	0.981	0.1119	0.741
690	108	10,023	0.1232	0.766	0.3533	0.395	0.0018	0.996	0.2345	0.569
720	91	10,040	0.1915	0.700	0.4796	0.336	0.0398	0.936	0.3295	0.504

Significant results are highlighted in gray.

Table 11. Tests for essential heterogeneity.

Outcome models being compared:

- ps: Only level two (outcome model) variables
- ps2: Level two variables plus propensity score (PS) interactions
- ps3: Level two variables, PS interactions, PS squared
- ps4: Level two variables, PS interactions, PS squared, PS cubed

Models with significant p-values are highlighted in gray.

Outcome model #1. Rearrest outcomes.

comparison	p-value	df	LRT stat	30 d
ps v. ps2	.7247282244852543	68	60.64817219923316	
ps2 v. ps3	.0499777483746286	1	3.842205207712141	
ps v. ps3	.6313676651018567	69	64.4903774069453	
ps3 v. ps4	.9923544494457799	1	.000091822835202	

comparison	p-value	df	LRT stat	60 d
ps v. ps2	.0073634753183159	68	99.7097151120015	
ps2 v. ps3	.3931413325206187	1	.7292039761960041	
ps v. ps3	.0080377199486241	69	100.4389190881975	
ps3 v. ps4	.6859455895396183	1	.1635096718910063	

comparison	p-value	df	LRT stat	90 d
ps v. ps2	.0013852449613909	68	108.2323149654294	
ps2 v. ps3	.0029898700399877	1	8.813639834430433	
ps v. ps3	.0002727927718945	69	117.0459547998598	
ps3 v. ps4	.0111951184249119	1	6.434079087955979	

comparison	p-value	df	LRT stat	120 d
ps v. ps2	.0005637886762719	68	112.4674146232628	
ps2 v. ps3	.0000549173675309	1	16.27032299052371	
ps v. ps3	.000017318763026	69	128.7377376137865	
ps3 v. ps4	.5909420006103214	1	.2888755597377894	

comparison	p-value	df	LRT stat	150 d
ps v. ps2	.0006588732162918	68	111.7474244308814	
ps2 v. ps3	.0032758988666004	1	8.647058053958972	
ps v. ps3	.000127450202238	69	120.3944824848404	
ps3 v. ps4	.658593402635154	1	.1952367363446683	

comparison	p-value	df	LRT stat	180 d
ps v. ps2	.0010027647965851	68	109.7782065284009	
ps2 v. ps3	.0164497400693443	1	5.754151308572546	
ps v. ps3	.000381710483412	69	115.5323578369735	
ps3 v. ps4	.4089768981509421	1	.6817729058075201	

comparison	p-value	df	LRT stat	210 d
ps v. ps2	.0010027647965851	68	109.7782065284009	
ps2 v. ps3	.0164497400693443	1	5.754151308572546	
ps v. ps3	.000381710483412	69	115.5323578369735	
ps3 v. ps4	.4089768981509421	1	.6817729058075201	

comparison	p-value	df	LRT stat	240 d
ps v. ps2	.0009817747882854	68	109.8784498735986	

ps2 v. ps3	.074514452596624	1	3.180663807945166	
ps v. ps3	.0006535717874361	69	113.0591136815437	
ps3 v. ps4	.9776559553886963	1	.000784435083915	

comparison	p-value	df	LRT stat	270 d
ps v. ps2	.0020582285655765	68	106.2977298204842	
ps2 v. ps3	.0421361317813183	1	4.129727642468424	
ps v. ps3	.0011402139991166	69	110.4274574629526	
ps3 v. ps4	.6762357653562577	1	.174394136049159	

comparison	p-value	df	LRT stat	300 d
ps v. ps2	.0037812881411134	68	103.2294707271194	
ps2 v. ps3	.030068516207043	1	4.705370725621833	
ps v. ps3	.0019018051781111	69	107.9348414527412	
ps3 v. ps4	.552591336691555	1	.3526953012042213	

comparison	p-value	df	LRT stat	330 d
ps v. ps2	.019015534269619	68	94.33731829819408	
ps2 v. ps3	.0145172375154234	1	5.974130487406001	
ps v. ps3	.0082262329877018	69	100.3114487856001	
ps3 v. ps4	.4558586060993994	1	.5560439381806646	

comparison	p-value	df	LRT stat	360 d
ps v. ps2	.0618980619731459	68	86.79137573507796	
ps2 v. ps3	.0094924184242932	1	6.727751502605315	
ps v. ps3	.026403066185915	69	93.51912723768328	
ps3 v. ps4	.6516483699474327	1	.2038282588309812	

Outcome model #1. Recidivism outcomes.

comparison	p-value	df	LRT stat	30 d
ps v. ps2	.873249778908923	68	54.948136122498	
ps2 v. ps3	.3403988475039348	1	.9089286189955601	
ps v. ps3	.8731082714078705	69	55.85706474149356	
ps3 v. ps4	.8800989154938205	1	.0227538591325356	

comparison	p-value	df	LRT stat	60 d
ps v. ps2	.0042380217580368	68	102.6397773053086	
ps2 v. ps3	.4421897310730704	1	.5905934394650103	
ps v. ps3	.0047830029301139	69	103.2303707447736	
ps3 v. ps4	.8425698418065506	1	.0394449108916888	

comparison	p-value	df	LRT stat	90 d
ps v. ps2	.0090000175559026	68	98.6122667245545	
ps2 v. ps3	.4629744933921253	1	.5386939669842832	
ps v. ps3	.0101375639197148	69	99.15096069153878	
ps3 v. ps4	.0014537396829266	1	10.13634704436299	

comparison	p-value	df	LRT stat	120 d
ps v. ps2	.0272863007808729	68	92.15004652874813	
ps2 v. ps3	.0226635556242213	1	5.194110131444177	
ps v. ps3	.013925719502702	69	97.34415666019231	
ps3 v. ps4	.0632944063518958	1	3.448886260490326	

comparison	p-value	df	LRT stat	150 d
ps v. ps2	.0602889745599804	68	86.97411031532465	
ps2 v. ps3	.0314928507241893	1	4.625893704027476	
ps v. ps3	.0357745308287799	69	91.60000401935213	
ps3 v. ps4	.6427426866258331	1	.2151730475306977	

comparison	p-value	df	LRT stat	180 d

ps v. ps2	.1354657331231485	68	80.91965786341825	
ps2 v. ps3	.0250598064080583	1	5.019748651244299	
ps v. ps3	.081635746343152	69	85.93940651466255	
ps3 v. ps4	.7739995130634999	1	.0824535892897984	

comparison	p-value	df	LRT stat	210 d
ps v. ps2	.1297818191391264	68	81.26722036427054	
ps2 v. ps3	.0629077388855319	1	3.45901605832114	
ps v. ps3	.0960351918042417	69	84.72623642259168	
ps3 v. ps4	.4385770100211271	1	.6000026630172215	

comparison	p-value	df	LRT stat	240 d
ps v. ps2	.1421285737239905	68	80.52591435311479	
ps2 v. ps3	.0745329585963803	1	3.18025804177887	
ps v. ps3	.1096436866856804	69	83.70617239489366	
ps3 v. ps4	.5817827143854477	1	.3033614709038375	

comparison	p-value	df	LRT stat	270 d
ps v. ps2	.2898873885316106	68	73.96072213480147	
ps2 v. ps3	.0790922606398188	1	3.083456771857527	
ps v. ps3	.2369681597423108	69	77.044178906659	
ps3 v. ps4	.8861876851861604	1	.0204861342299409	

comparison	p-value	df	LRT stat	300 d
ps v. ps2	.3331684078828728	68	72.45870330276557	
ps2 v. ps3	.0596073477690238	1	3.548276105340847	
ps v. ps3	.2631298926871957	69	76.00697940810642	
ps3 v. ps4	.938996285235467	1	.0058570644978317	

comparison	p-value	df	LRT stat	330 d
ps v. ps2	.4470672744157994	68	68.88933766136142	
ps2 v. ps3	.0278649145431451	1	4.836405749103506	
ps v. ps3	.3263834811911357	69	73.72574341046493	
ps3 v. ps4	.930405327423431	1	.0076273817649053	

comparison	p-value	df	LRT stat	360 d
ps v. ps2	.5005400092216298	68	67.3188138507212	
ps2 v. ps3	.0267528536129231	1	4.906690465750216	
ps v. ps3	.3718415124665846	69	72.22550431647142	
ps3 v. ps4	.6792145624325571	1	.171011334467039	

Outcome model #2. Rearrest outcomes.

comparison	p-value	df	LRT stat	30 d
ps v. ps2	.6341961413914275	71	66.34769741171203	
ps2 v. ps3	.0815192017697536	1	3.03434982633371	
ps v. ps3	.5655683421891279	72	69.38204723804574	
ps3 v. ps4	.2532002018934728	1	1.305559536945111	

comparison	p-value	df	LRT stat	60 d
ps v. ps2	.0893206139522504	71	87.5006594965962	
ps2 v. ps3	.1001738769685425	1	2.702773015877028	
ps v. ps3	.0721878105821004	72	90.20343251247323	
ps3 v. ps4	.7551828575855737	1	.0972271714781527	

comparison	p-value	df	LRT stat	90 d
ps v. ps2	.0534369068513583	71	91.21297340822093	
ps2 v. ps3	.0535505333066178	1	3.726655025280706	
ps v. ps3	.03641830674487	72	94.93962843350164	
ps3 v. ps4	.1218334575981155	1	2.393591260914036	

comparison	p-value	df	LRT stat	120 d
ps v. ps2	.0491432931403505	71	91.78834659174754	
ps2 v. ps3	.0198824683986739	1	5.422184542110699	
ps v. ps3	.0255743968614229	72	97.21053113385824	
ps3 v. ps4	.9372064517385101	1	.0062065182901279	

comparison	p-value	df	LRT stat	150 d
ps v. ps2	.0732146326867188	71	88.97802224166844	
ps2 v. ps3	.1229124286869727	1	2.379810846699911	
ps v. ps3	.0615155683508351	72	91.35783308836835	
ps3 v. ps4	.6457660352033199	1	.2112799520491535	

comparison	p-value	df	LRT stat	180 d
ps v. ps2	.1105637642280466	71	85.84859181700995	
ps2 v. ps3	.1851093399157665	1	1.75611895532893	
ps v. ps3	.1017862594877711	72	87.60471077233888	
ps3 v. ps4	.6290067870425506	1	.2334100337611744	

comparison	p-value	df	LRT stat	210 d
ps v. ps2	.1024131476917372	71	86.45013752505838	
ps2 v. ps3	.4812953558052726	1	.4959267628128146	
ps v. ps3	.1106370813648233	72	86.9460642878712	
ps3 v. ps4	.4774478037660458	1	.5046872268521838	

comparison	p-value	df	LRT stat	240 d
ps v. ps2	.0960756937601363	71	86.94443472976491	
ps2 v. ps3	.7602993675706724	1	.0930784977390431	
ps v. ps3	.1093735700124302	72	87.03751322750395	
ps3 v. ps4	.7048415040414431	1	.1434842203561857	

comparison	p-value	df	LRT stat	270 d
ps v. ps2	.1352410066199308	71	84.21489403990927	
ps2 v. ps3	.7984324275764469	1	.0652170852517884	
ps v. ps3	.1526374558429111	72	84.28011112516106	
ps3 v. ps4	.8999888963453597	1	.0157942995156191	

comparison	p-value	df	LRT stat	300 d
ps v. ps2	.1916489121197597	71	81.17904401440865	
ps2 v. ps3	.9937744359475715	1	.0000608816062595	
ps v. ps3	.214861126766433	72	81.17910489601491	
ps3 v. ps4	.9038381668335926	1	.0145960818081221	

comparison	p-value	df	LRT stat	330 d
ps v. ps2	.3129938911117198	71	76.26973814975281	
ps2 v. ps3	.7405255652610261	1	.109665250789476	
ps v. ps3	.3397595409181237	72	76.37940340054229	
ps3 v. ps4	.8135972306896071	1	.055595950303541	

comparison	p-value	df	LRT stat	360 d
ps v. ps2	.4368822212616864	71	72.2341825983458	
ps2 v. ps3	.9444614309870697	1	.0048530142539676	
ps v. ps3	.4699185758609322	72	72.23903561259976	
ps3 v. ps4	.9574495663065186	1	.0028466880685301	

Outcome model #2. Recidivism outcomes.

comparison	p-value	df	LRT stat	30 d
ps v. ps2	.9383639673014026	71	53.61664359154565	
ps2 v. ps3	.2113240722714267	1	1.562332169634828	
ps v. ps3	.9294865304607938	72	55.17897576118048	
ps3 v. ps4	.0808591171424778	1	3.047548377905514	

comparison	p-value	df	LRT stat	60 d
ps v. ps2	.0135961481925384	71	99.85653662332879	
ps2 v. ps3	.6900365388779264	1	.1590458108912571	
ps v. ps3	.0161716042867643	72	100.0155824342201	
ps3 v. ps4	.9796001091757441	1	.0006538380821439	

comparison	p-value	df	LRT stat	90 d
ps v. ps2	.0253810313291002	71	96.09438250442872	
ps2 v. ps3	.1787127394467108	1	1.808296303965108	
ps v. ps3	.0228898968008918	72	97.90267880839383	
ps3 v. ps4	.1059743293946452	1	2.613250708009218	

comparison	p-value	df	LRT stat	120 d
ps v. ps2	.0832611604391269	71	88.02903730364415	
ps2 v. ps3	.0122917503649541	1	6.26829301741418	
ps v. ps3	.0401297113674184	72	94.29733032105833	
ps3 v. ps4	.9531595589648606	1	.0034503344977566	

comparison	p-value	df	LRT stat	150 d
ps v. ps2	.1442093726505706	71	83.67717751403325	
ps2 v. ps3	.0457154212273295	1	3.992049664502701	
ps v. ps3	.1009500997023657	72	87.66922717853595	
ps3 v. ps4	.2657841157242836	1	1.23837678851487	

comparison	p-value	df	LRT stat	180 d
ps v. ps2	.21812330997519	71	79.96916245022476	
ps2 v. ps3	.0659077843380533	1	3.382106099776138	
ps v. ps3	.1697257377301008	72	83.3512685500009	
ps3 v. ps4	.1093379633468886	1	2.5637642878919	

comparison	p-value	df	LRT stat	210 d
ps v. ps2	.227019072804088	71	79.58459792518079	
ps2 v. ps3	.3649739973851827	1	.8207054232225346	
ps v. ps3	.2327027387975313	72	80.40530334840332	
ps3 v. ps4	.0555342643654488	1	3.665971334727146	

comparison	p-value	df	LRT stat	240 d
ps v. ps2	.2455274537619131	71	78.81436226184087	
ps2 v. ps3	.5428850777964709	1	.3702187077888084	
ps v. ps3	.2627043066859431	72	79.18458096962968	
ps3 v. ps4	.2932589055396707	1	1.104599555128516	

comparison	p-value	df	LRT stat	270 d
ps v. ps2	.3577005375334557	71	74.74448801701328	
ps2 v. ps3	.5523048631005164	1	.3532042487386207	
ps v. ps3	.3783088269705727	72	75.0976922657519	
ps3 v. ps4	.8450301893305968	1	.0382059398707497	

comparison	p-value	df	LRT stat	300 d
ps v. ps2	.5063017937732053	71	70.14741464570216	
ps2 v. ps3	.3491713293789225	1	.8764664164755231	
ps v. ps3	.510394750525224	72	71.02388106217768	
ps3 v. ps4	.7738932991452228	1	.0825332775348215	

comparison	p-value	df	LRT stat	330 d
ps v. ps2	.6864988505440716	71	64.73168466039169	
ps2 v. ps3	.1355369691026672	1	2.22791122682429	
ps v. ps3	.6459219118603183	72	66.95959588721598	
ps3 v. ps4	.7311514004047714	1	.1180570535489096	

comparison	p-value	df	LRT stat	360 d
ps v. ps2	.7538620204332558	71	62.50749908783291	

ps2 v. ps3	.1486673570945478	1	2.085871496279651
ps v. ps3	.7202785785068799	72	64.59337058411256
ps3 v. ps4	.7368247250865758	1	.1129371224433271

Chapter 9 Tables

Table 12. Average treatment effect and average prison peer effect estimates from the local instrumental variables analysis implemented with *margte*.

	120-Day Threshold				**150-Day Threshold**				**180-Day Threshold**			
	Average treatment effects											
	Model #1		***Model #2***		***Model #1***		***Model #2***		***Model #1***		***Model #2***	
	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism
	0.0100	0.0511	0.0025	0.0431	-0.0150	0.0362	-0.0249	0.0250	-0.0252	-0.0140	-0.0341	0.0164
	(0.749)	(0.092)	(0.936)	(0.152)	(0.556)	(0.172)	(0.335)	(0.362)	(0.411)	(0.765)	(0.259)	(0.584)
	Average treatment effects as moderated by prior incarceration											
	Model #1		***Model #2***		***Model #1***		***Model #2***		***Model #1***		***Model #2***	
value	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism
0	-0.0095	0.0391	-0.0172	0.0309	-0.0300	0.0291	-0.0398	0.0180	-0.0437	0.0165	-0.0524	0.0056
	(0.771)	(0.136)	(0.603)	(0.368)	(0.349)	(0.328)	(0.266)	(0.439)	(0.269)	(0.586)	(0.170)	(0.867)
1	0.0563	**0.0795**	0.0093	**0.0721**	0.0204	**0.0531**	0.0104	0.0417	0.0188	0.0535	0.0493	0.0420
	(0.132)	**(0.017)**	(0.806)	**(0.022)**	(0.613)	**(0.033)**	(0.770)	(0.275)	(0.637)	(0.171)	(0.148)	(0.256)
	Average treatment effects as moderated by relative prior arrest											
	Model #1		***Model #2***		***Model #1***		***Model #2***		***Model #1***		***Model #2***	
value	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism
-8	0.0007	0.0580	0.0021	**0.0609**	-0.0133	0.0442	-0.0254	0.0350	0.0338	0.0284	-0.0370	0.0211
	(0.984)	(0.101)	(0.954)	**(0.041)**	(0.642)	(0.226)	(0.432)	(0.237)	(0.320)	(0.426)	(0.333)	(0.606)
-6	0.0028	0.0565	0.0022	0.0569	-0.0137	0.0424	-0.0253	0.0327	-0.0319	0.0282	-0.0364	0.0200
	(0.926)	(0.060)	(0.935)	(0.119)	(0.658)	(0.175)	(0.441)	(0.319)	(0.385)	(0.449)	(0.315)	(0.553)
-4	0.0049	**0.0549**	0.0023	0.0529	-0.0141	0.0406	-0.0252	0.0305	-0.0299	0.0280	-0.0357	0.0190

	(0.849)	**(0.044)**	(0.930)	(0.062)	(0.670)	(0.226)	(0.450)	(0.268)	(0.449)	(0.417)	(0.224)	(0.581)
-2	0.0070	0.0533	0.0024	0.0489	-0.0145	0.0388	-0.0251	0.0282	-0.0280	0.0278	-0.0351	0.0179
	(0.801)	(0.094)	(0.933)	(0.067)	(0.631)	(0.206)	(0.408)	(0.270)	(0.408)	(0.379)	(0.172)	(0.639)
0	0.0091	0.0518	0.0025	0.0448	-0.0149	0.0370	-0.0249	0.0260	-0.0260	0.0276	-0.0344	0.0169
	0.7360	0.0580	0.9350	0.0770	0.5160	0.1980	0.4380	0.3220	0.5460	0.4100	0.3760	0.5580
2	0.0112	0.0502	0.0026	0.0408	-0.0152	0.0352	-0.0248	0.0237	-0.0240	0.0273	-0.0337	0.0158
	(0.646)	(0.055)	(0.936)	(0.191)	(0.614)	(0.190)	(0.405)	(0.431)	(0.371)	(0.402)	(0.211)	(0.653)
4	0.0133	**0.0486**	0.0027	0.0368	-0.0156	0.0334	-0.0247	0.0215	-0.0221	0.0271	-0.0331	0.0148
	(0.638)	**(0.052)**	(0.932)	(0.232)	(0.640)	(0.226)	(0.465)	(0.453)	(0.415)	(0.477)	(0.379)	(0.673)
6	0.0155	0.0471	0.0028	0.0328	-0.0160	0.0315	-0.0246	0.0192	-0.0201	0.0269	-0.0324	0.0137
	(0.652)	(0.138)	(0.933)	(0.298)	(0.599)	(0.334)	(0.357)	(0.539)	(0.472)	(0.450)	(0.380)	(0.692)
8	0.0176	0.0455	0.0029	0.0288	-0.0164	0.0297	-0.0245	0.0170	-0.0181	0.0267	-0.0317	0.0127
	(0.620)	(0.097)	(0.937)	(0.407)	(0.645)	(0.390)	(0.537)	(0.570)	(0.665)	(0.507)	(0.392)	(0.734)
10	0.0197	0.0439	0.0030	0.0247	-0.0168	0.0279	-0.0244	0.0147	-0.0162	0.0265	-0.0311	0.0116
	(0.558)	(0.193)	(0.928)	(0.470)	(0.657)	(0.362)	(0.517)	(0.661)	(0.640)	(0.517)	(0.414)	(0.791)
	Average treatment effects as moderated by relative risk scores											
	Model #1		***Model #2***		***Model #1***		***Model #2***		***Model #1***		***Model #2***	
value	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism	rearrest	recidivism
-4			-0.0372	-0.0020			-0.0087	0.0252			-0.0641	0.0036
			(0.572)	(0.976)			(0.887)	(0.704)			(0.355)	(0.964)
-3			-0.0279	0.0086			-0.0125	0.0251			-0.0571	0.0066
			(0.639)	(0.881)			(0.816)	(0.618)			(0.239)	(0.904)
-2			-0.0186	0.0191			-0.0163	0.0251			-0.0501	0.0096
			(0.658)	(0.680)			(0.693)	(0.565)			(0.224)	(0.861)
-1			-0.0093	0.0297			-0.0201	0.0251			-0.0431	0.0126
			(0.739)	(0.359)			(0.575)	(0.465)			(0.275)	(0.773)

0		(0.000)	(0.040)		-(0.024)	(0.025)		-(0.036)	(0.016)
		(0.999)	(0.185)		(0.251)	(0.411)		(0.266)	(0.651)
1		0.0093	0.0508		-0.0276	0.0250		-0.0290	0.0186
		(0.811)	(0.094)		(0.293)	(0.325)		(0.368)	(0.607)
2		0.0186	0.0613		-0.0314	0.0250		-0.0220	0.0216
		(0.621)	(0.079)		(0.446)	(0.494)		(0.519)	(0.565)
3		0.0278	0.0719		-0.0352	0.0249		-0.0150	0.0246
		(0.570)	(0.055)		(0.446)	(0.658)		(0.774)	(0.669)
4		0.0371	0.0824		-0.0390	0.0249		-0.0079	0.0276
		(0.559)	(0.188)		(0.558)	(0.661)		(0.886)	(0.674)

Bolded effects are significant at $p<0.05$. p-vales in (). Dark gray = Increasing ATEs/Higher ATE. Light gray = Decreasing ATEs/Lower ATE

Table 13. Cross tabulation, relative prior arrest.

rel_pri_narr	Freq.	Percent	Cum.
-45	1	0.01	0.01
-41	1	0.01	0.02
-39	1	0.01	0.03
-38	1	0.01	0.04
-37	1	0.01	0.05
-33	1	0.01	0.06
-29	3	0.03	0.09
-27	2	0.02	0.11
-26	2	0.02	0.13
-25	3	0.03	0.16
-24	7	0.07	0.23
-23	2	0.02	0.25
-22	5	0.05	0.30
-21	11	0.11	0.40
-20	10	0.10	0.50
-19	10	0.10	0.60
-18	13	0.13	0.73
-17	16	0.16	0.89
-16	26	0.26	1.15
-15	27	0.27	1.41
-14	31	0.31	1.72
-13	48	0.47	2.19
-12	56	0.55	2.74
-11	58	0.57	3.32
-10	92	0.91	4.22
-9	130	1.28	5.51
-8	169	1.67	7.18
-7	211	2.08	9.26
-6	293	2.89	12.15
-5	369	3.64	15.79
-4	467	4.61	20.40
-3	613	6.05	26.45
-2	719	7.10	33.55
-1	801	7.91	41.46
0	1,006	9.93	51.39
1	853	8.42	59.81
2	742	7.32	67.13
3	596	5.88	73.01
4	520	5.13	78.15
5	384	3.79	81.94
6	324	3.20	85.13
7	255	2.52	87.65
8	231	2.28	89.93
9	186	1.84	91.77
10	140	1.38	93.15
11	114	1.13	94.27
12	98	0.97	95.24
13	76	0.75	95.99
14	64	0.63	96.62
15	48	0.47	97.10
16	46	0.45	97.55
17	39	0.38	97.94
18	29	0.29	98.22
19	27	0.27	98.49
20	27	0.27	98.76
21	17	0.17	98.92
22	19	0.19	99.11
23	12	0.12	99.23
24	10	0.10	99.33
25	6	0.06	99.39
26	10	0.10	99.49
27	11	0.11	99.60
28	2	0.02	99.62
29	1	0.01	99.62
30	2	0.02	99.64
31	2	0.02	99.66
32	5	0.05	99.71
33	2	0.02	99.73
34	3	0.03	99.76
35	2	0.02	99.78
36	3	0.03	99.81
37	3	0.03	99.84

38	1	0.01	99.85
39	1	0.01	99.86
40	3	0.03	99.89
41	2	0.02	99.91
42	2	0.02	99.93
43	2	0.02	99.95
46	3	0.03	99.98
63	1	0.01	99.99
71	1	0.01	100.00
Total	10,131	100.00	

Table 14. Cross tabulation, relative risk score.

rel_rsth	Freq.	Percent	Cum.
-7	2	0.02	0.02
-6	10	0.10	0.12
-5	51	0.50	0.62
-4	191	1.89	2.51
-3	532	5.25	7.76
-2	1,053	10.39	18.15
-1	1,596	15.75	33.91
0	2,105	20.78	54.68
1	1,961	19.36	74.04
2	1,315	12.98	87.02
3	832	8.21	95.23
4	346	3.42	98.65
5	120	1.18	99.83
6	16	0.16	99.99
7	1	0.01	100.00
Total	10,131	100.00	

FIGURES

Chapter 5 Figures

Figure 1. Map of PADOC facilities and their associated prison industries.

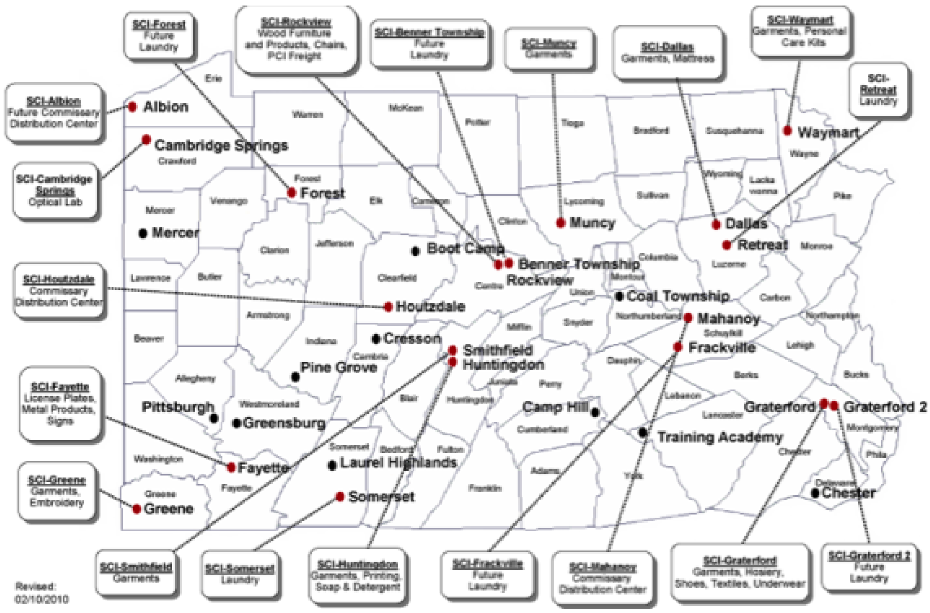

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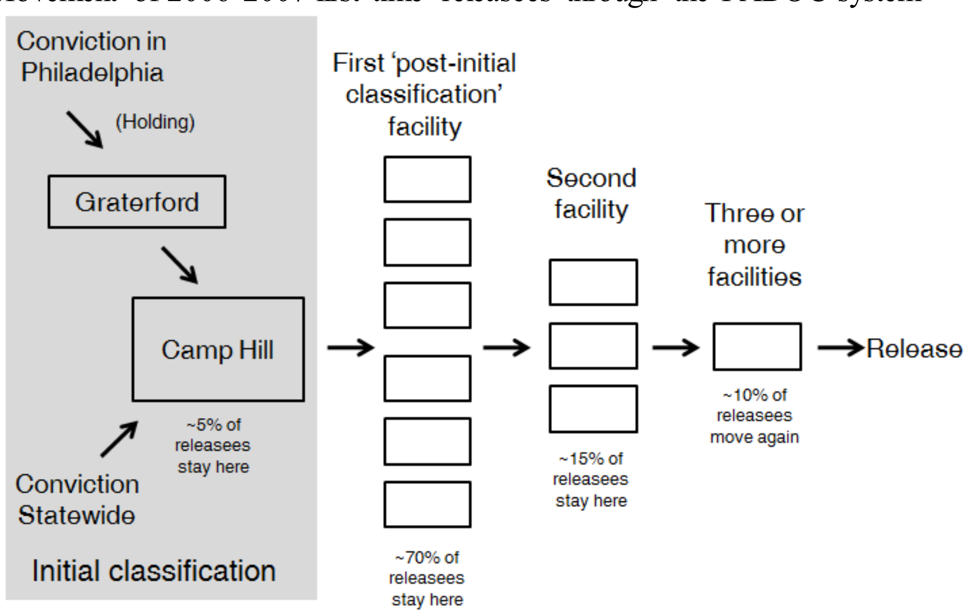
Figure 2. Movement of 2006-2007 first-time releasees through the PADOC system



Chapter 8 Figures

Figure 3. Initial choice and outcome model specifications.

Choice model:
Days with cellmate = A + C(releasee characteristics) + D(cellmate characteristics) + E(prior incarceration and releasee level and relative prior arrest) + G(other variables) + H(cellmate similarity variables) + I(facility fixed effects) + J(potential instruments) + U

Outcome model #1 (Prior arrest social interactions):
Reoffending = A + B(days with cellmate) + C(releasee characteristics) + D(cellmate characteristics) + E(Prior incarceration and releasee level and relative prior arrest) + F(pool characteristics) + G(other variables) + H(cellmate similarity variables) + I(facility fixed effects) + J(potential instruments) + U

Outcome model #2 (All social interactions):
Reoffending = A + B(days with cellmate) + C(releasee characteristics) + D(cellmate characteristics) + E(all social interaction variables) + F(pool characteristics) + G(other variables) + H(cellmate similarity variables) + I(facility fixed effects) + J(potential instruments) + U

Figure 4. Steps used to detect essential heterogeneity in the relationship between having a criminogenic cellmate and rearrest.

Steps to Test for Essential Heterogeneity

1. Using *probit* regression, estimate the full first-stage choice model where the outcome is the duration of cellmate association;
2. Predict the probability of celling with a cellmate for a particular amount of time. This is the propensity score;
3. Estimate the second-stage outcome model, with terms for the propensity score, the level 2 regressors, interactions between the level 2 regressors and the propensity score, the propensity score squared, and the propensity score cubed added sequentially;
4. Calculate the joint significance of each of the added terms using likelihood ratio tests. If the terms are significant, nonlinearities are present and essential heterogeneity is relevant to the study of cellmate social interactions.

Chapter 9 Figures

Common support of the propensity score graphs.

Figure 5. Common support of the propensity score at the 60-day threshold.

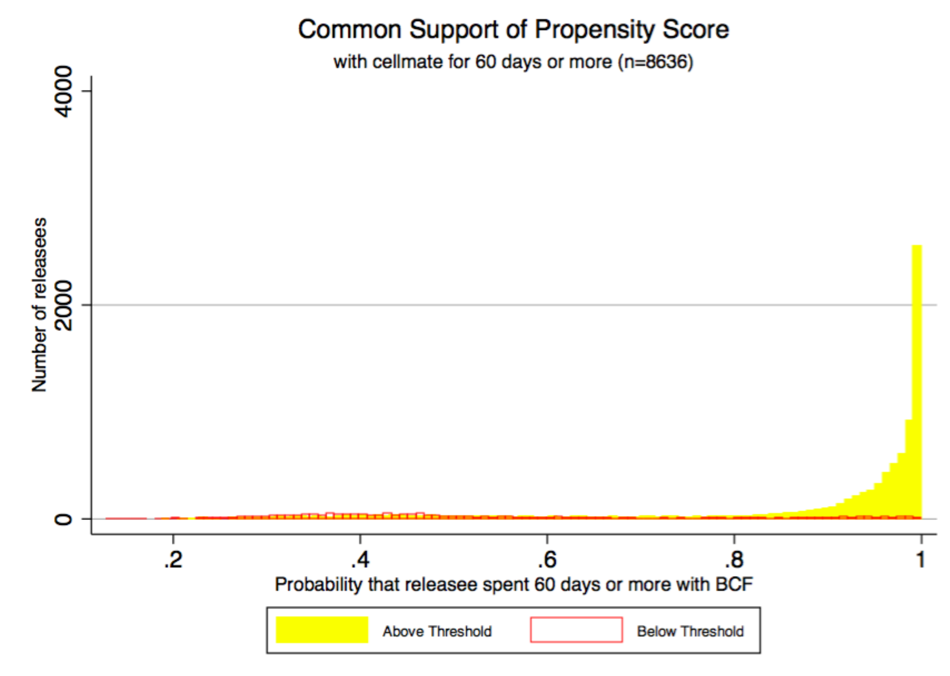


Figure 6. Common support of the propensity score at the 90-day threshold.

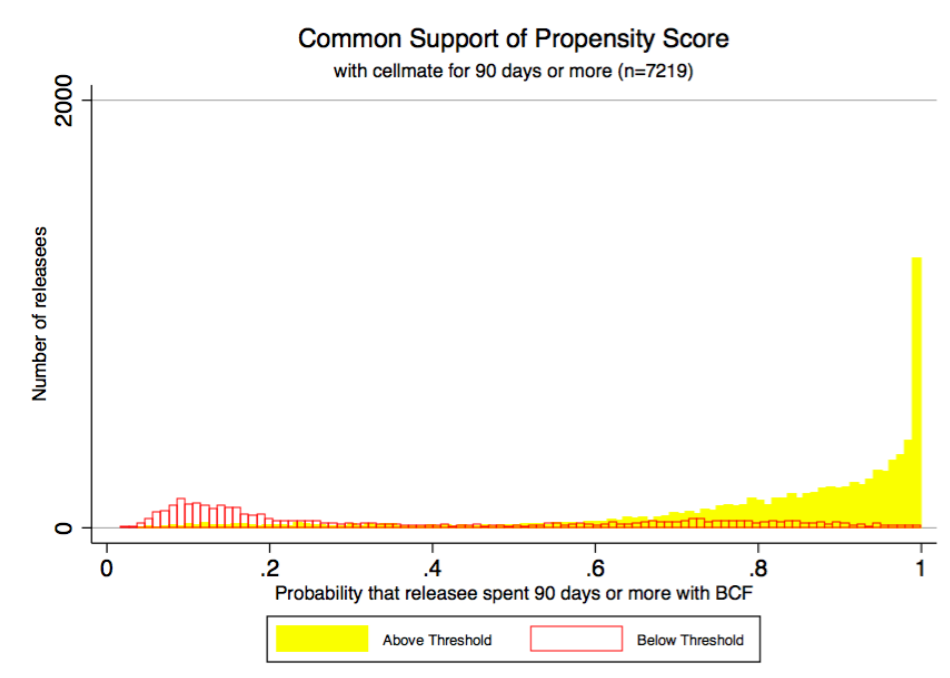


Figure 7. Common support of the propensity score at the 120-day threshold.

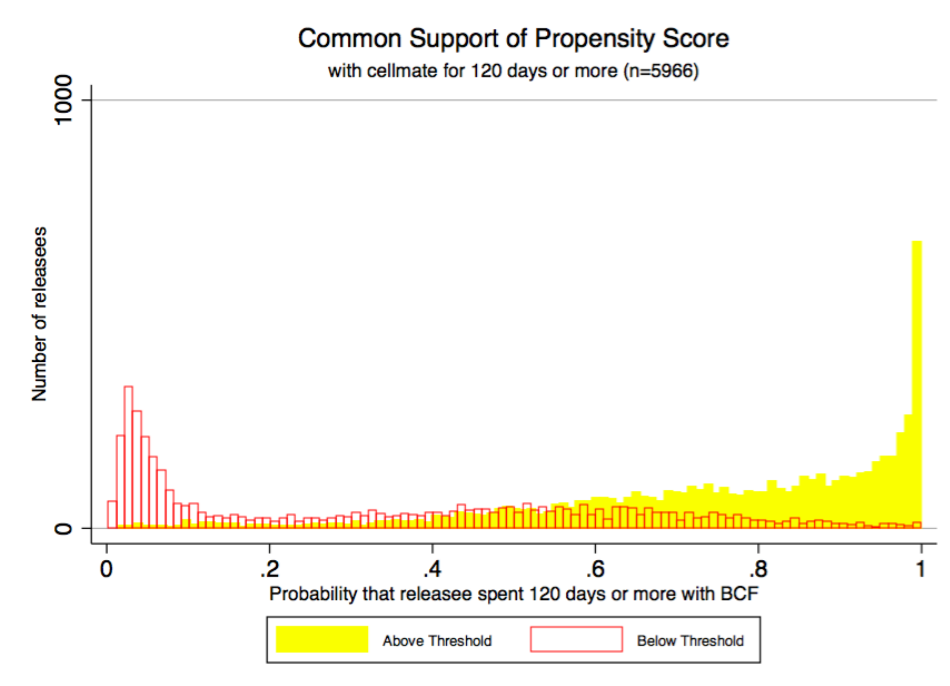


Figure 8. Common support of the propensity score at the 150-day threshold.

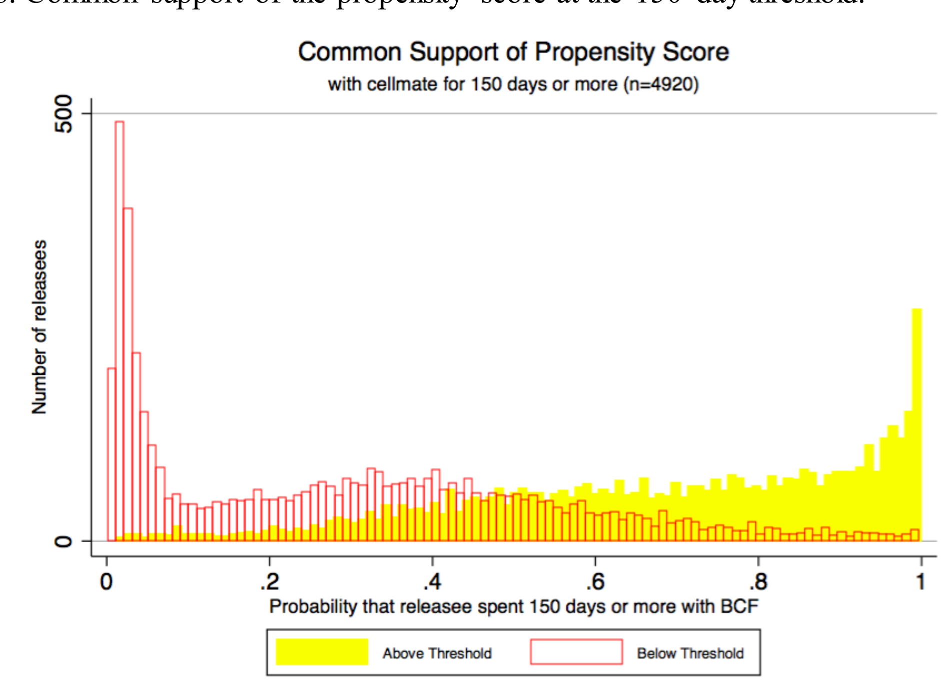


Figure 9. Common support of the propensity score at the 180-day threshold.

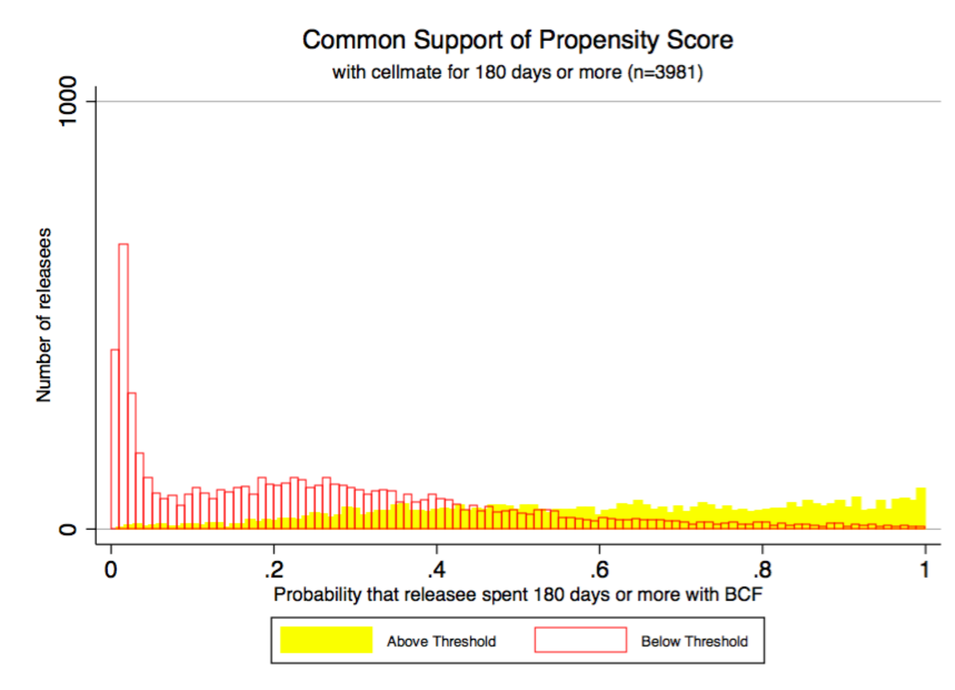


Figure 10. Common support of the propensity score at the 210-day threshold.

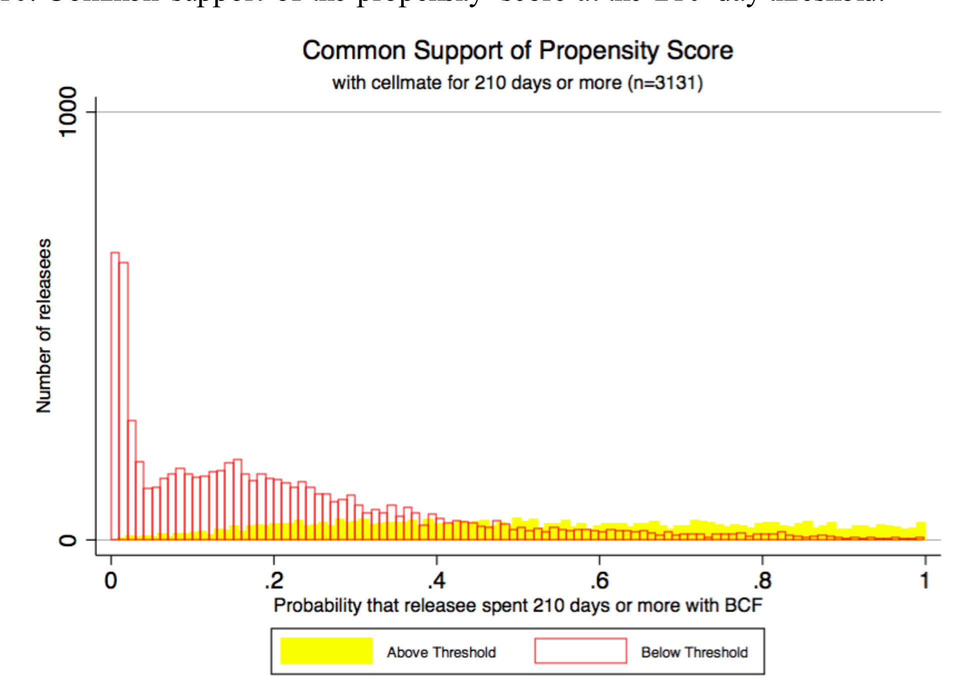
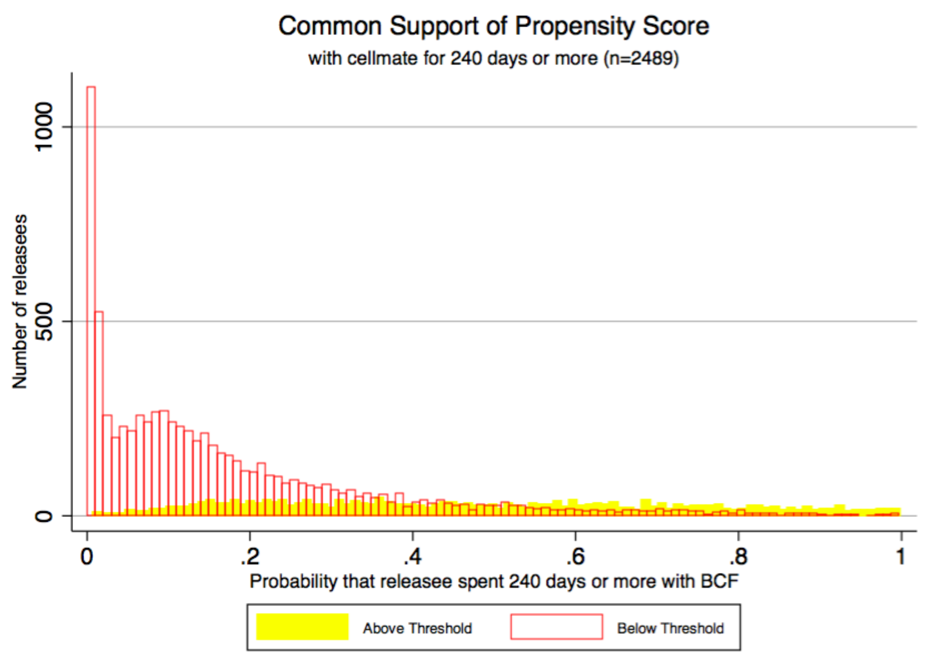


Figure 11. Common support of the propensity score at the 240-day threshold.



Interpreting MTEs.

Figure 12. Guide to interpretation of treatment effect graphs.

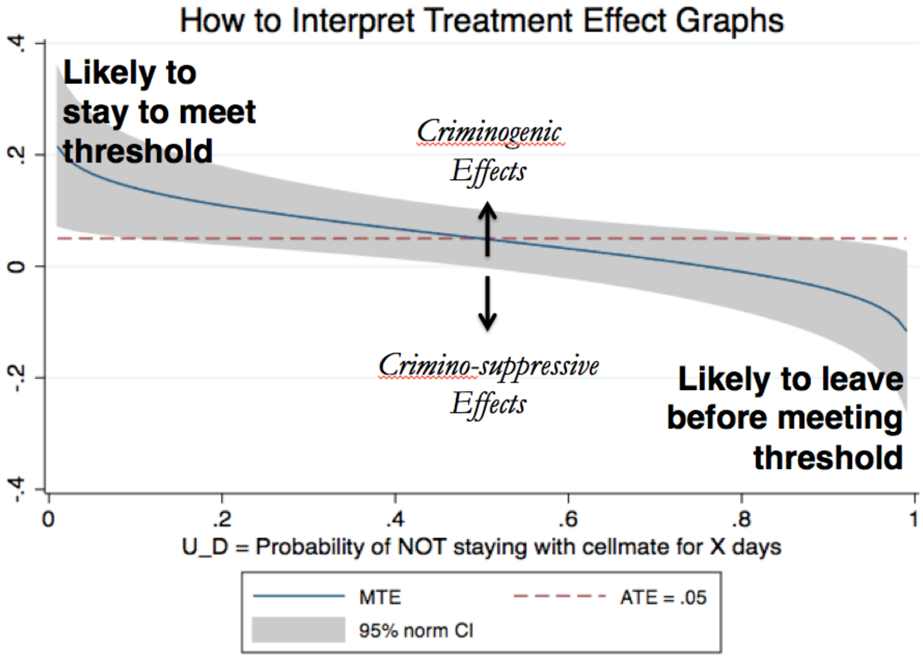
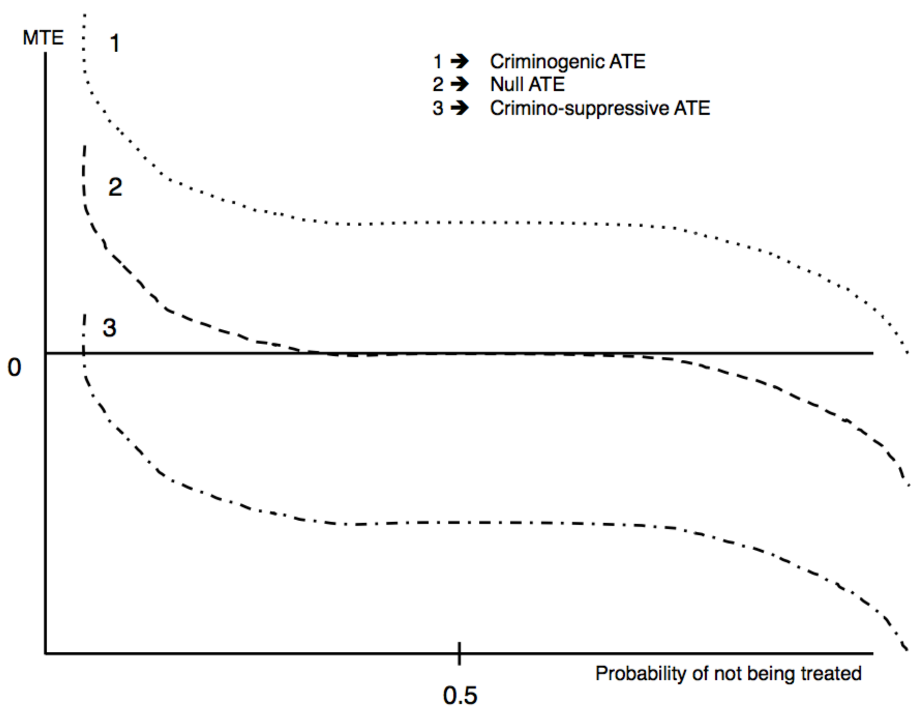


Figure 13. Potential MTE and ATE curves for criminogenic, crimino-suppressive, and null effects.



Average and marginal treatment effect graphs for outcome model #1.

Figure 14. Average and marginal treatment effects on rearrest at the 120-day threshold from outcome model #1.

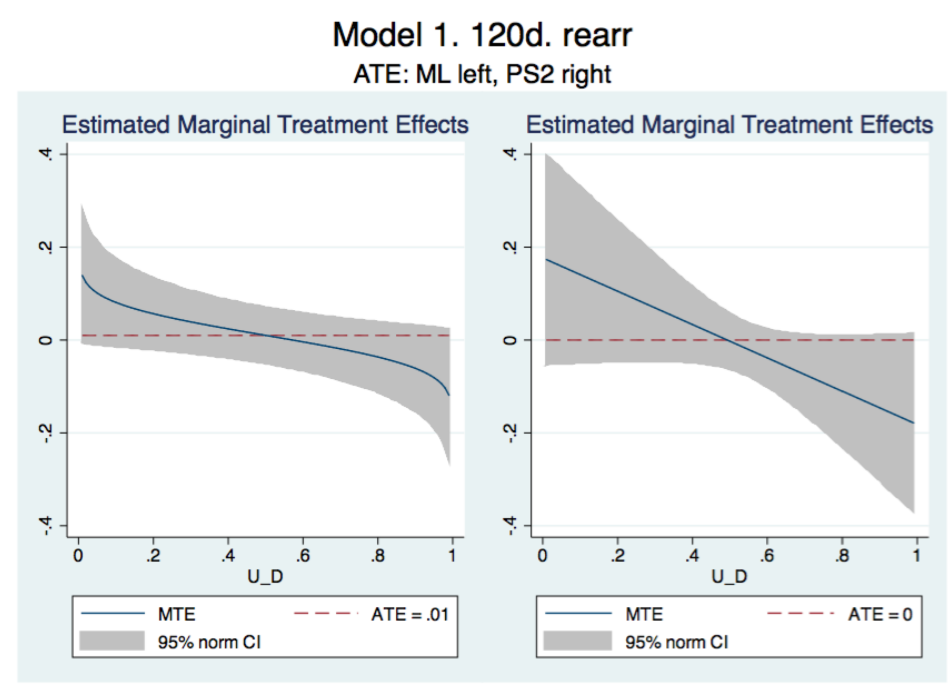


Figure 15. Average and marginal treatment effects on rearrest at the 150-day threshold from outcome model #1.

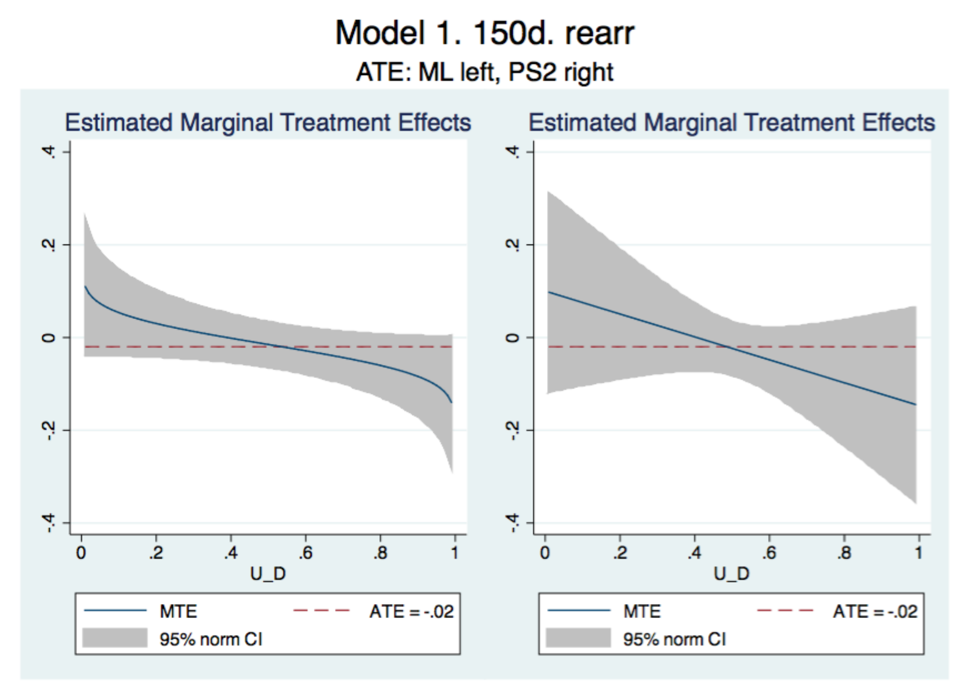


Figure 16. Average and marginal treatment effects on rearrest at the 180-day threshold from outcome model #1.

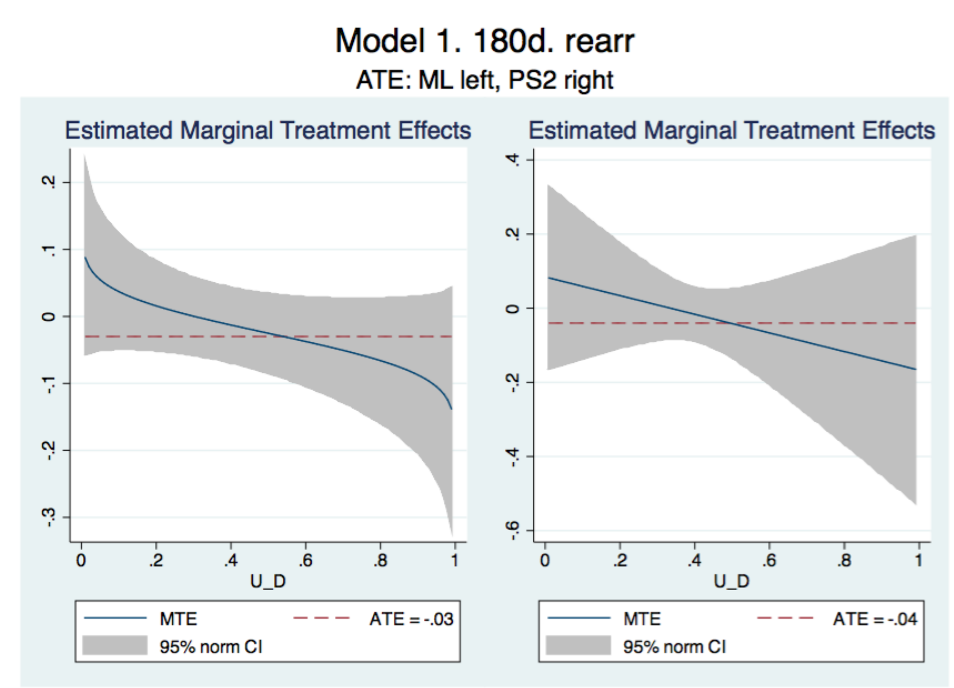


Figure 17. Average and marginal treatment effects on recidivism at the 120-day threshold from outcome model #1.

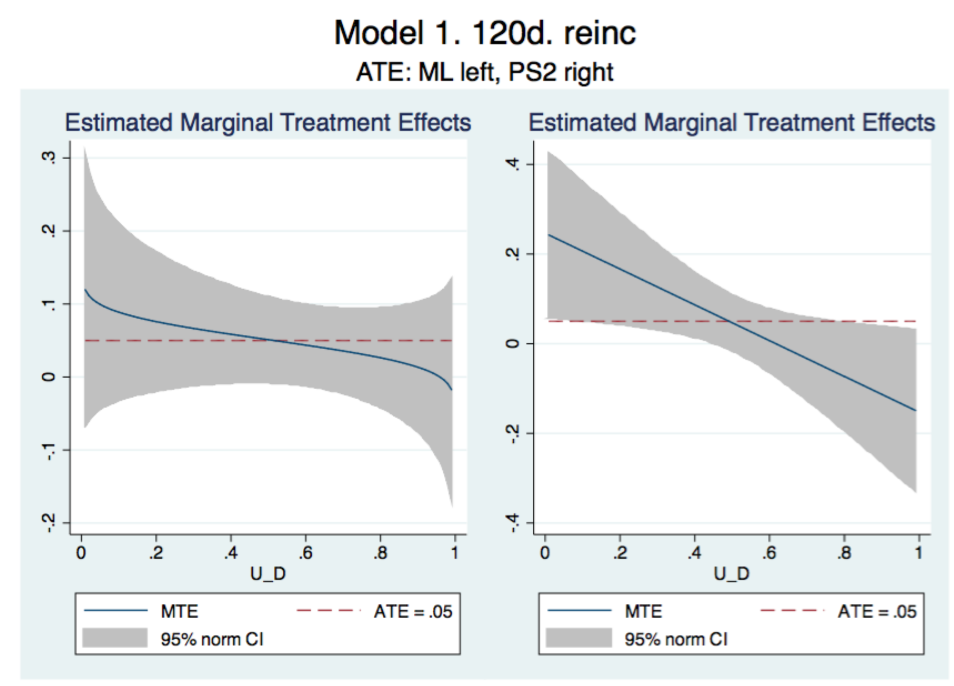


Figure 18. Average and marginal treatment effects on recidivism at the 150-day threshold from outcome model #1.

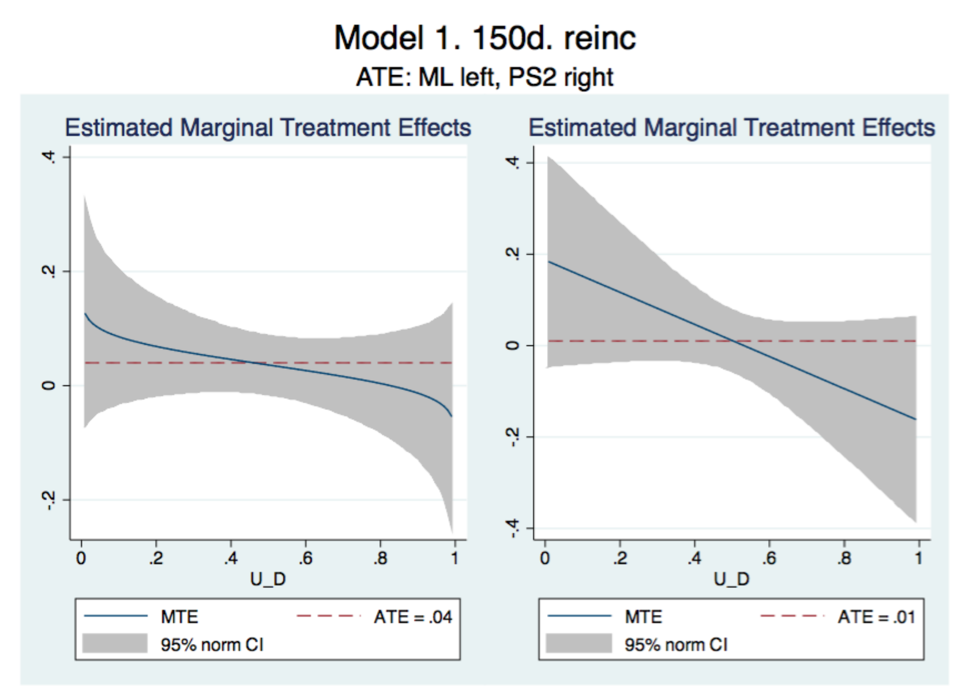
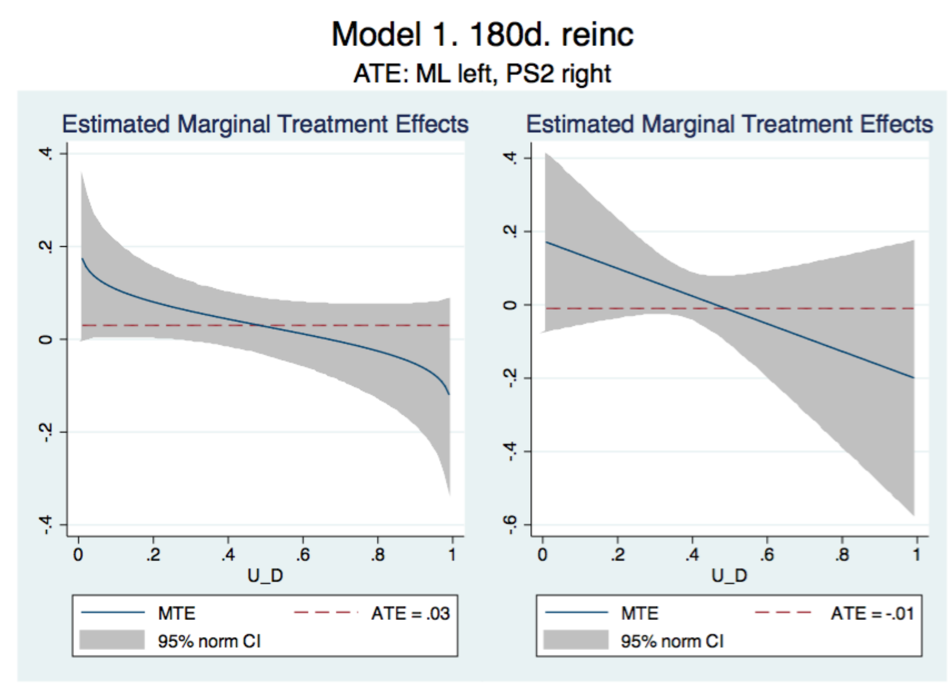


Figure 19. Average and marginal treatment effects on recidivism at the 180-day threshold from outcome model #1.



Average and marginal treatment effect graphs for outcome model #2.

Figure 20. Average and marginal treatment effects on rearrest at the 120-day threshold from outcome model #2.

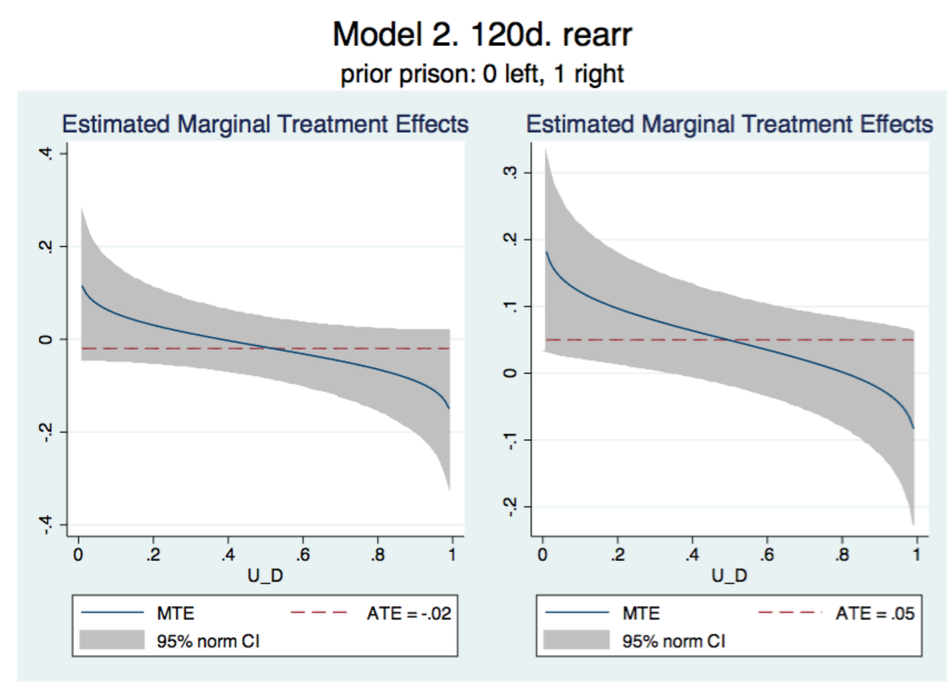


Figure 21. Average and marginal treatment effects on rearrest at the 150-day threshold from outcome model #2.

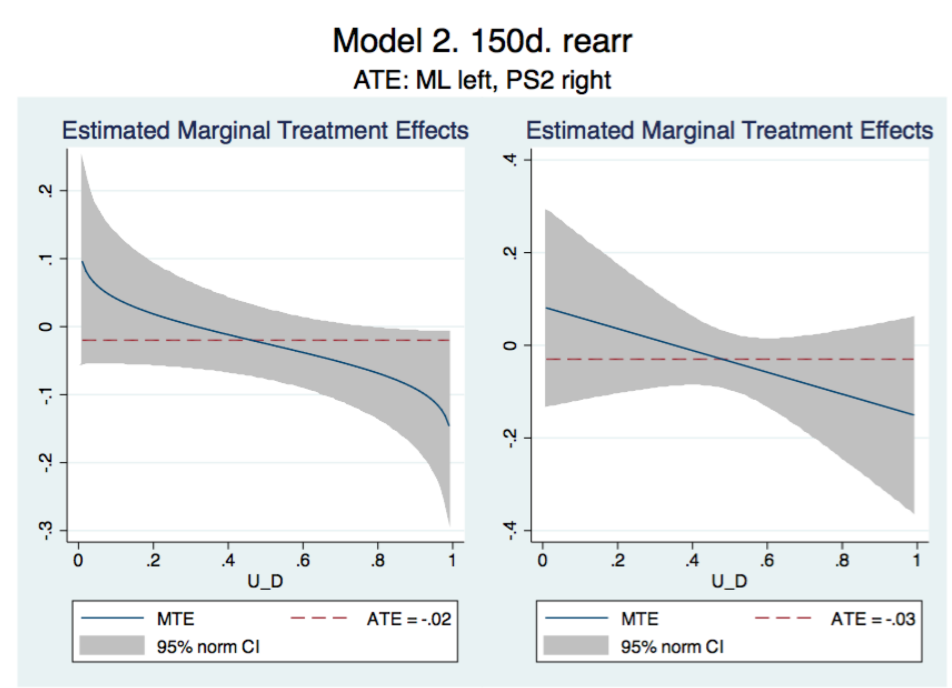


Figure 22. Average and marginal treatment effects on rearrest at the 180-day threshold from outcome model #2.

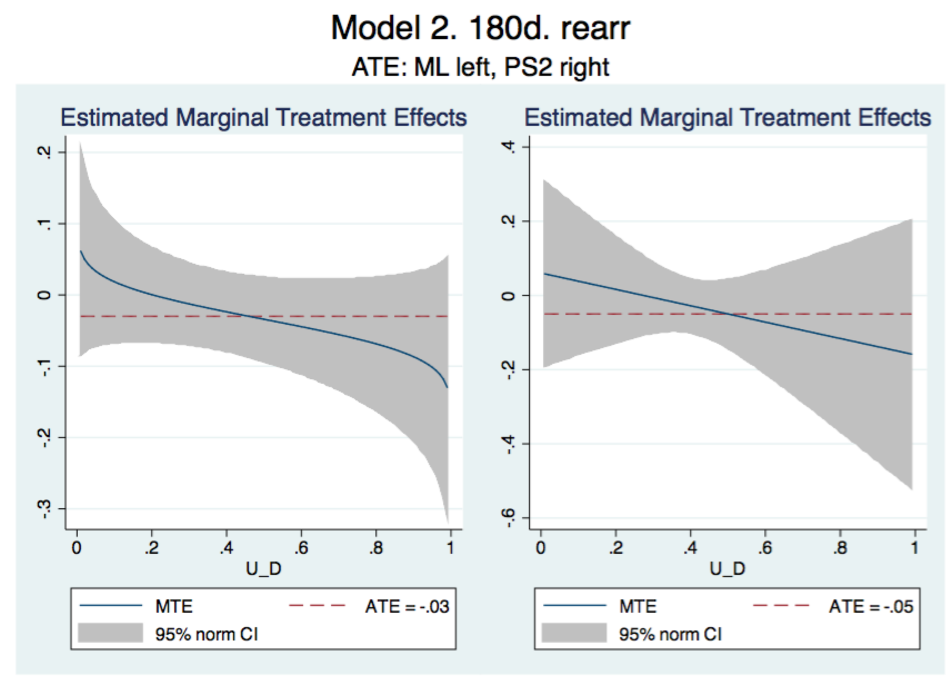


Figure 23. Average and marginal treatment effects on recidivism at the 120-day threshold from outcome model #2.

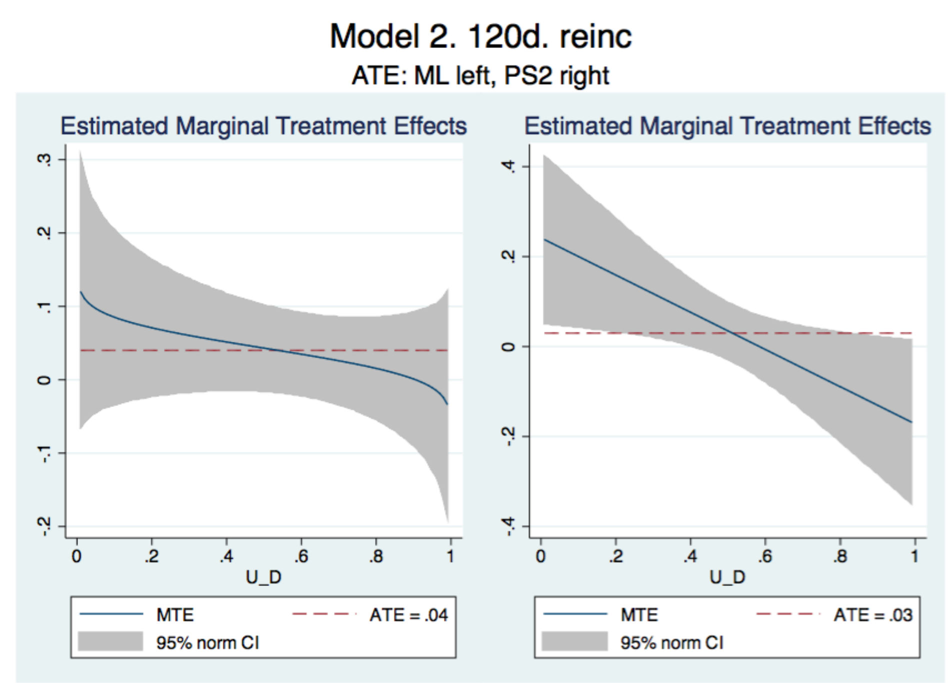


Figure 24. Average and marginal treatment effects on recidivism at the 150-day threshold from outcome model #2.

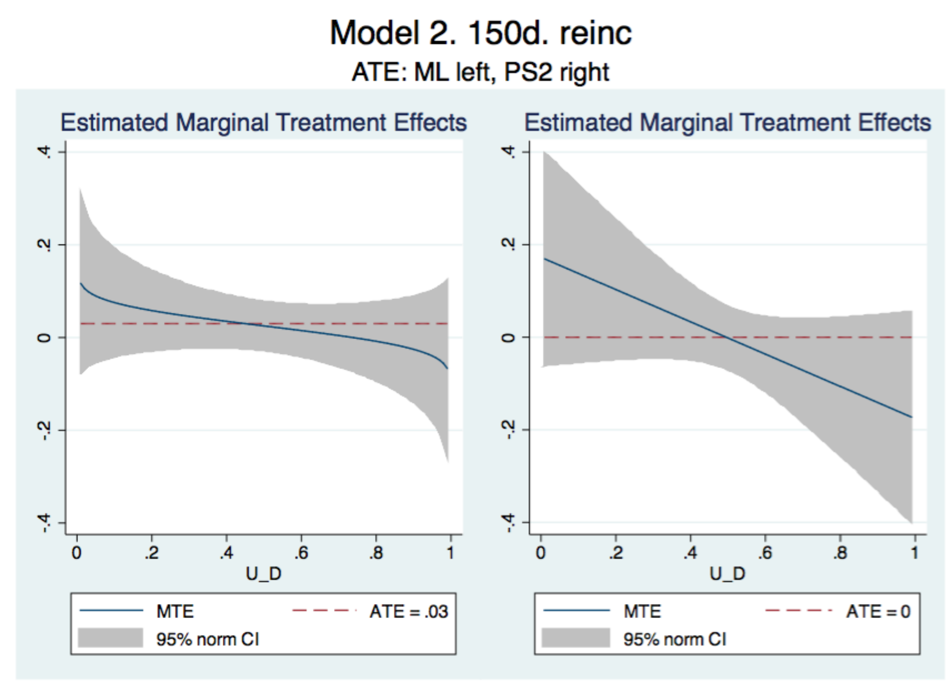
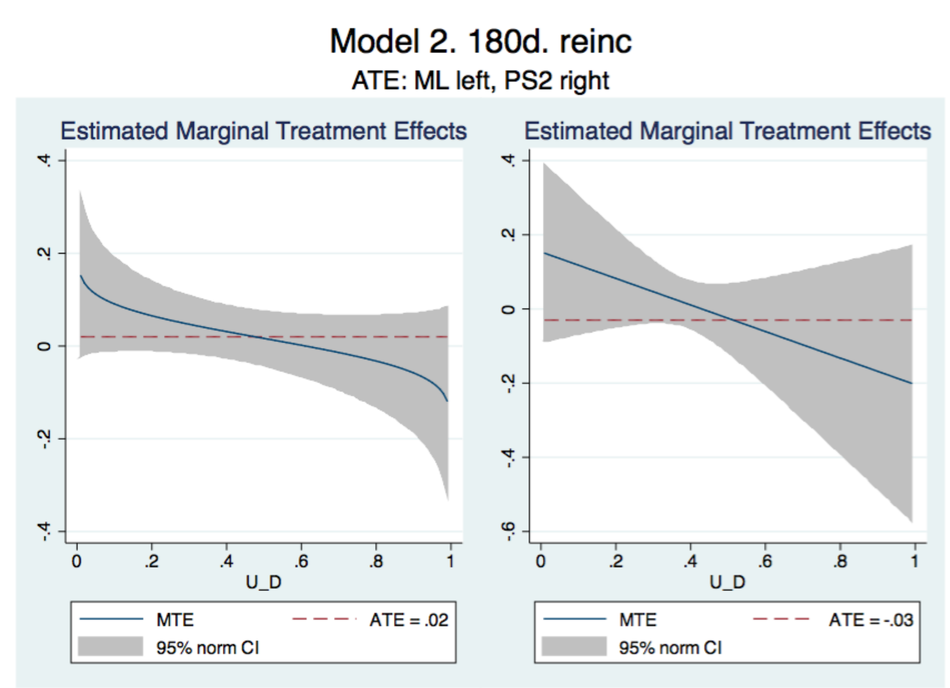


Figure 25. Average and marginal treatment effects on recidivism at the 180-day threshold from outcome model #2.



Average and marginal treatment effect graphs for outcome model for prior incarceration in outcome model #1.

Figure 26. Average and marginal prison peer effects of cellmate prior incarceration on releasees' rearrest at the 120-day threshold, outcome model #1.

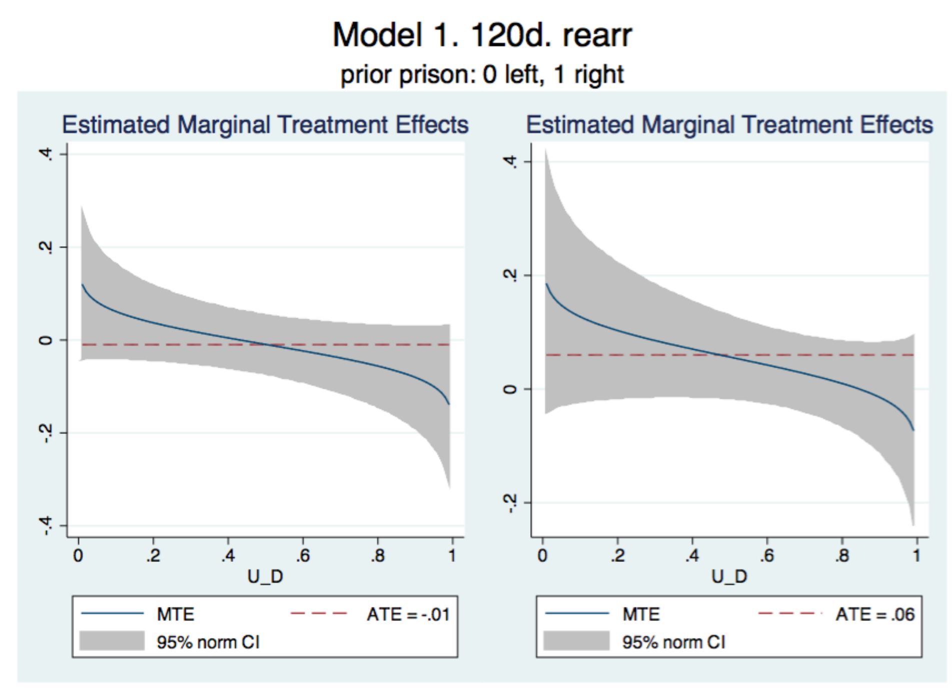


Figure 27. Average and marginal prison peer effects of cellmate prior incarceration on releasees' rearrest at the 150-day threshold, outcome model #1.

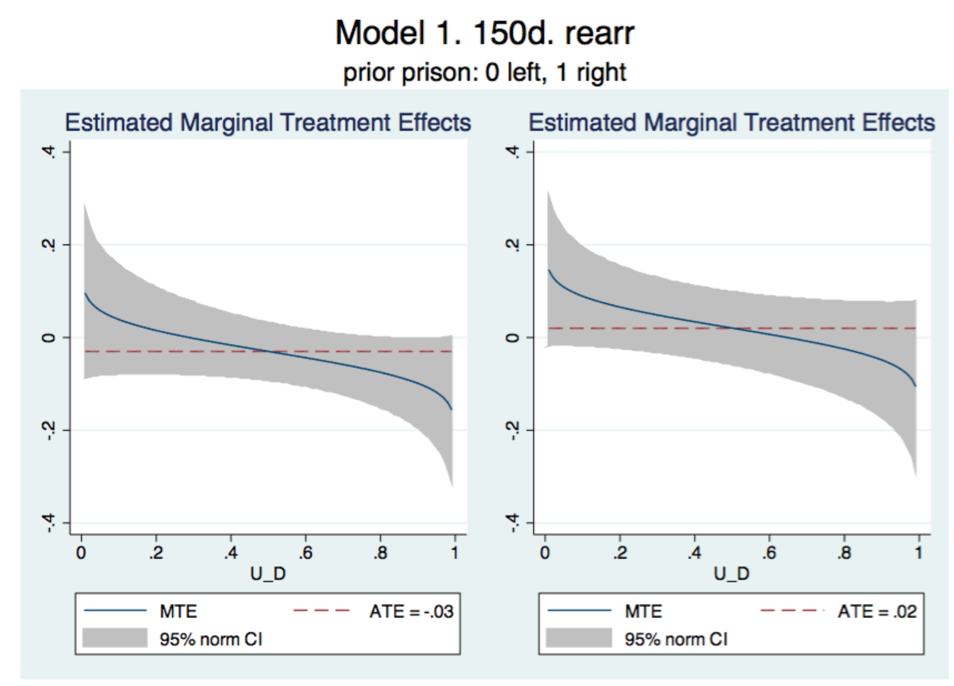


Figure 28. Average and marginal prison peer effects of cellmate prior incarceration on releasees' rearrest at the 180-day threshold, outcome model #1.

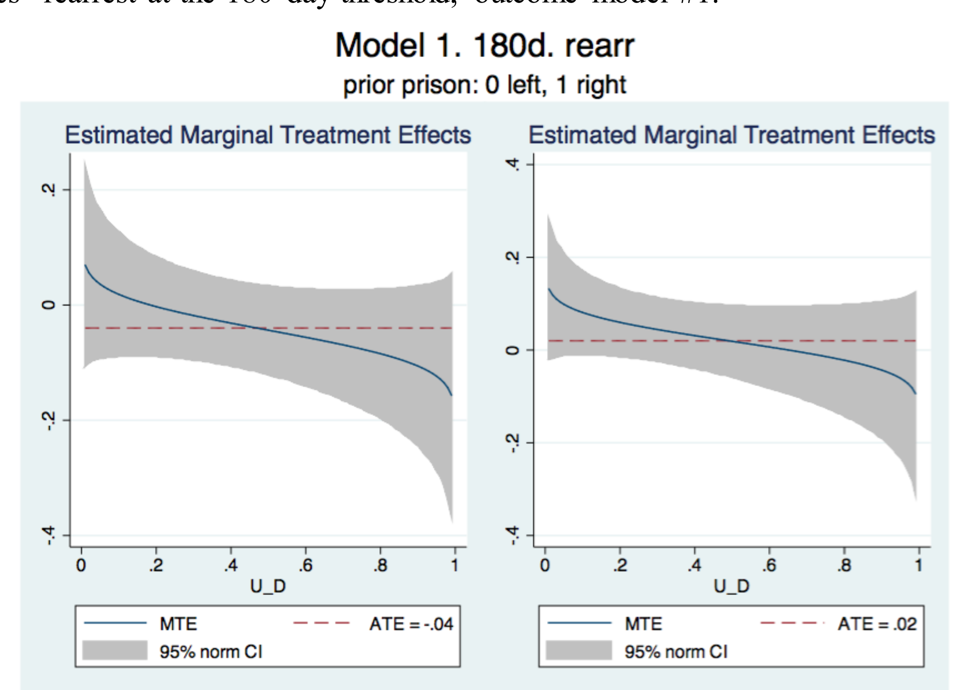


Figure 29. Average and marginal prison peer effects of cellmate prior incarceration on releasees' recidivism at the 120-day threshold, outcome model #1.

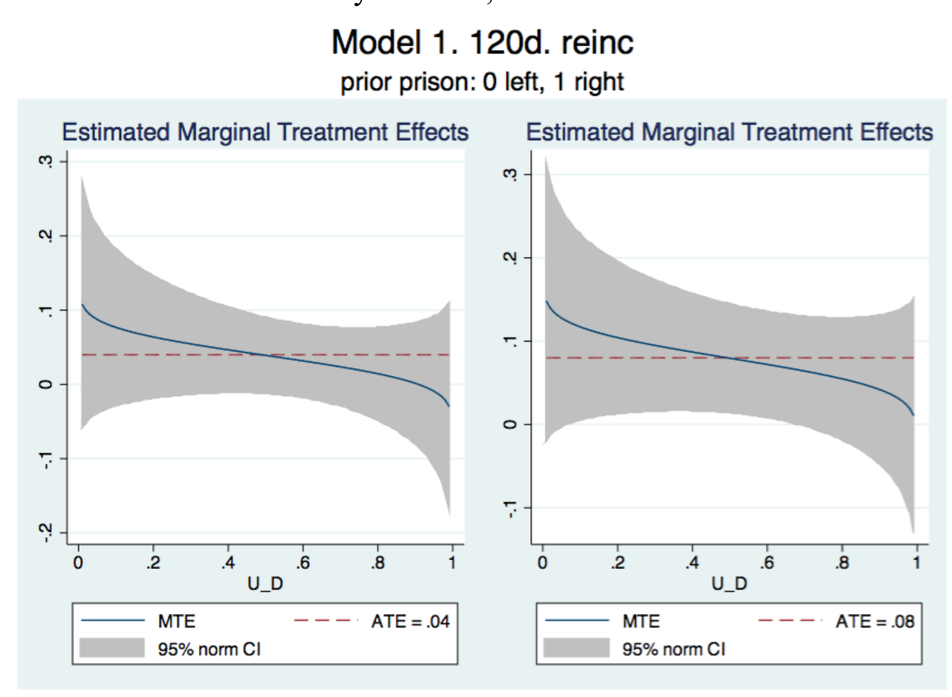


Figure 30. Average and marginal prison peer effects of cellmate prior incarceration on releasees' recidivism at the 150-day threshold, outcome model #1.

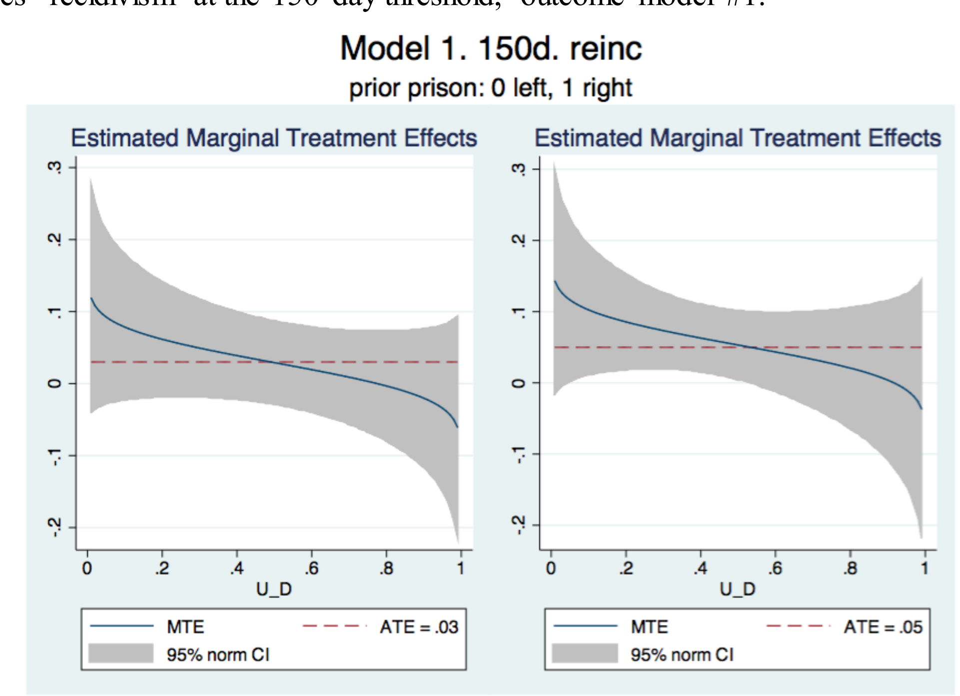
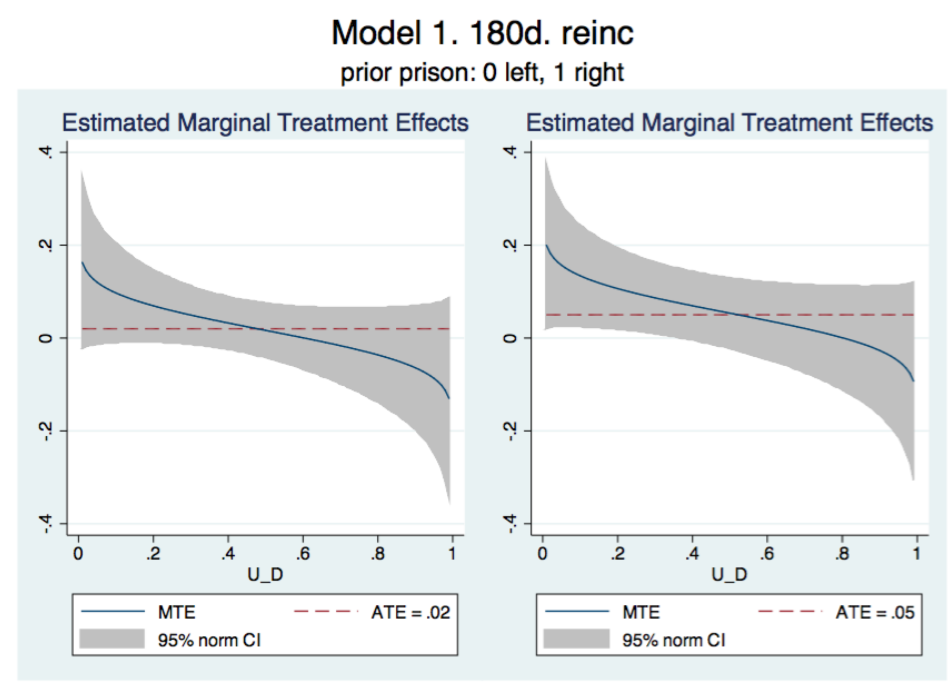


Figure 31. Average and marginal prison peer effects of cellmate prior incarceration on releasees' recidivism at the 180-day threshold, outcome model #1.



Average and marginal treatment effect graphs for outcome model for prior incarceration in outcome model #2.

Figure 32. Average and marginal prison peer effects of cellmate prior incarceration on releasees' rearrest at the 120-day threshold, outcome model #2.

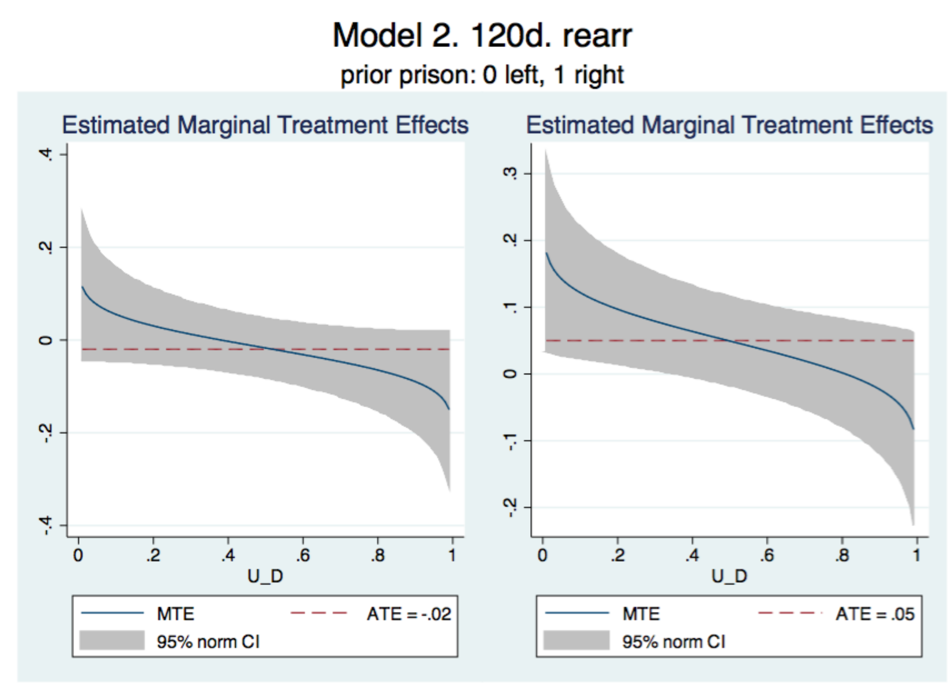


Figure 33. Average and marginal prison peer effects of cellmate prior incarceration on releasees' rearrest at the 150-day threshold, outcome model #2.

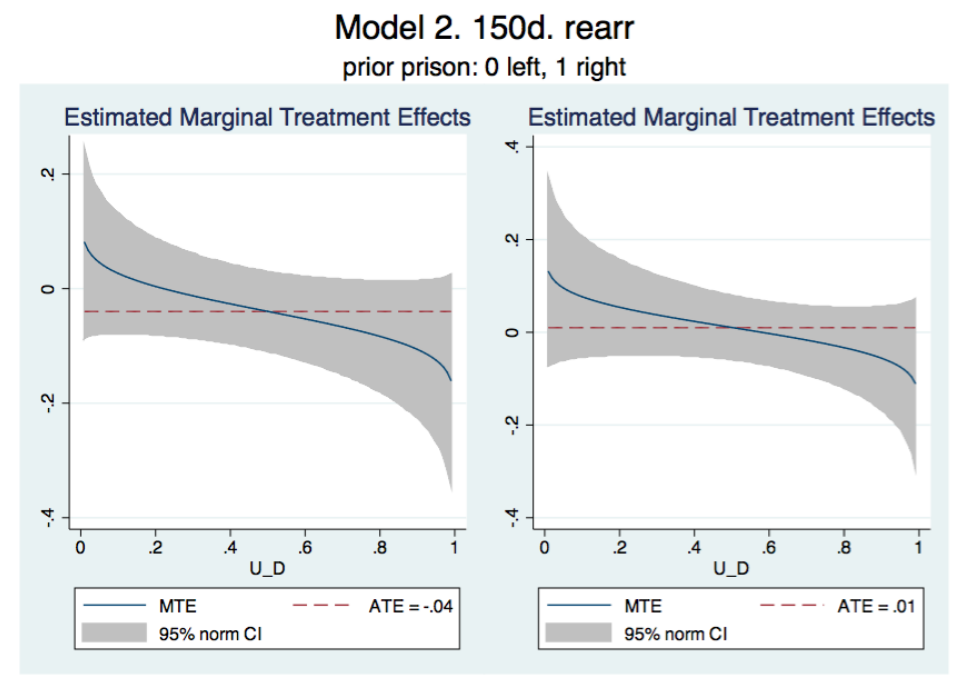


Figure 34. Average and marginal prison peer effects of cellmate prior incarceration on releasees' rearrest at the 180-day threshold, outcome model #2.

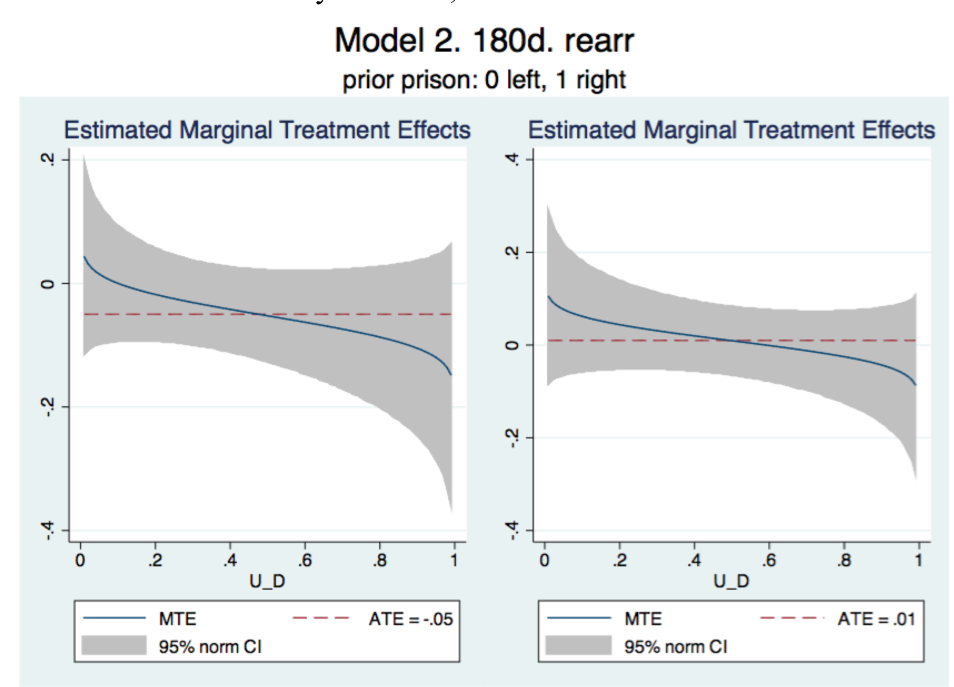


Figure 35. Average and marginal prison peer effects of cellmate prior incarceration on releasees' recidivism at the 120-day threshold, outcome model #2.

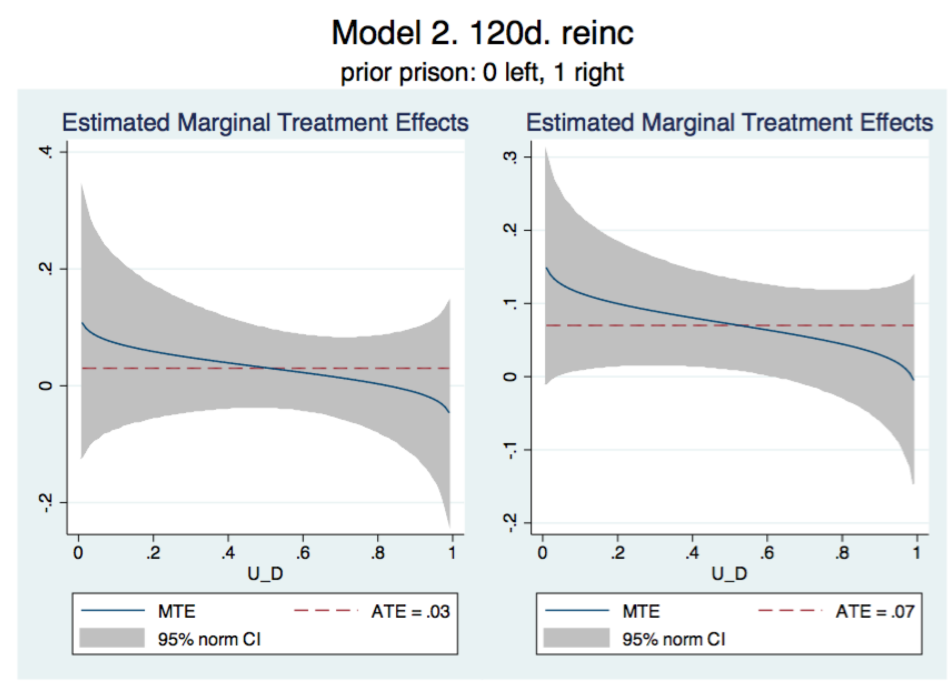


Figure 36. Average and marginal prison peer effects of cellmate prior incarceration on releasees' recidivism at the 150-day threshold, outcome model #2.

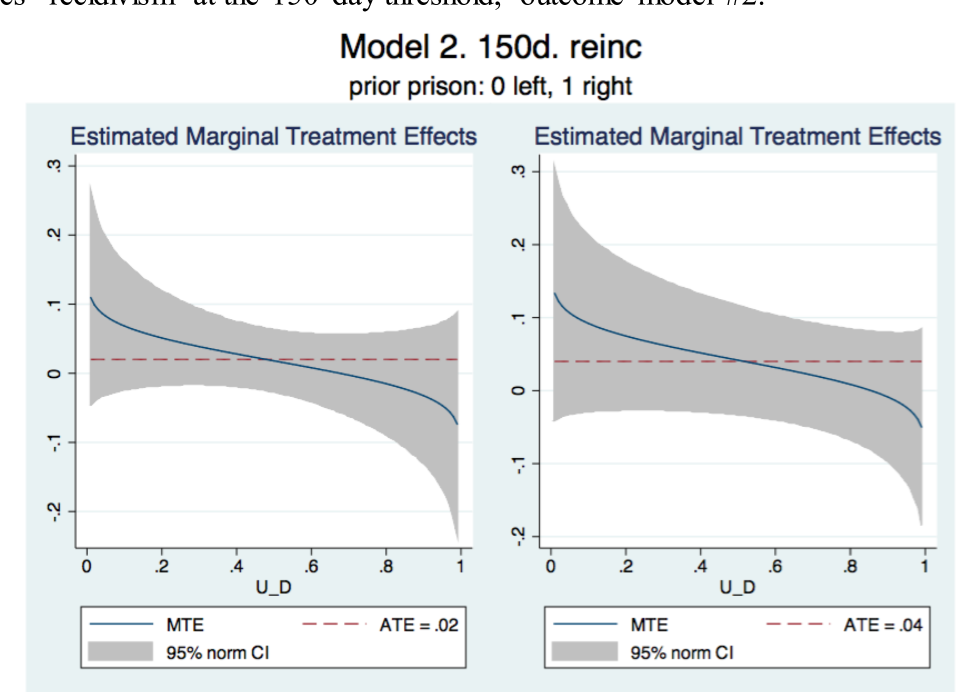
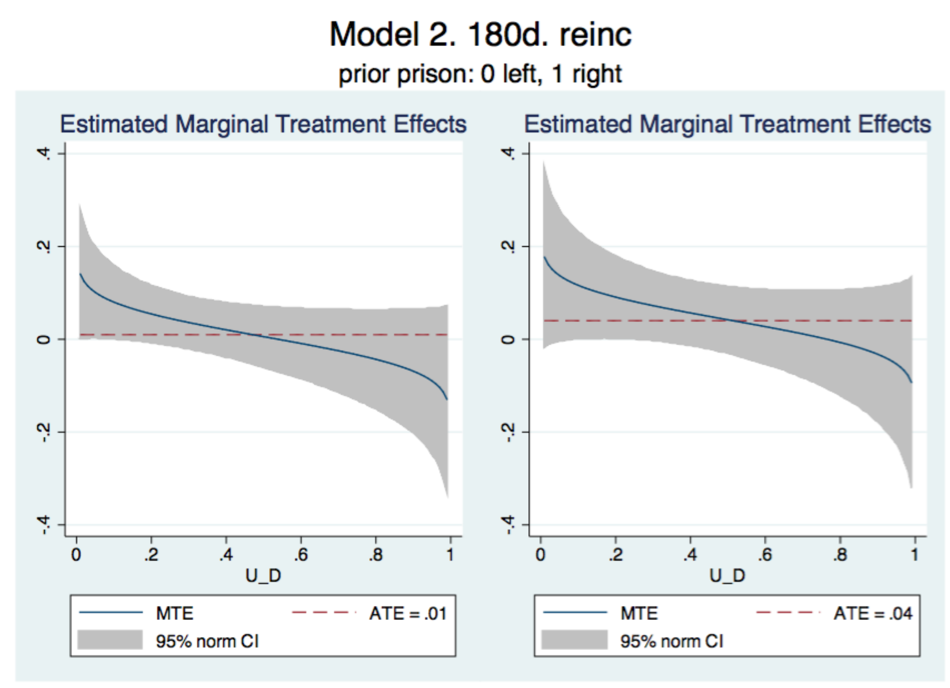


Figure 37. Average and marginal prison peer effects of cellmate prior incarceration on releasees' recidivism at the 180-day threshold, outcome model #2.



Average and marginal prison peer effect graphs for prior arrest in outcome model #1.

Figure 38. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 120-day threshold, outcome model #1, relative arrest = -6 and relative arrest = +6.

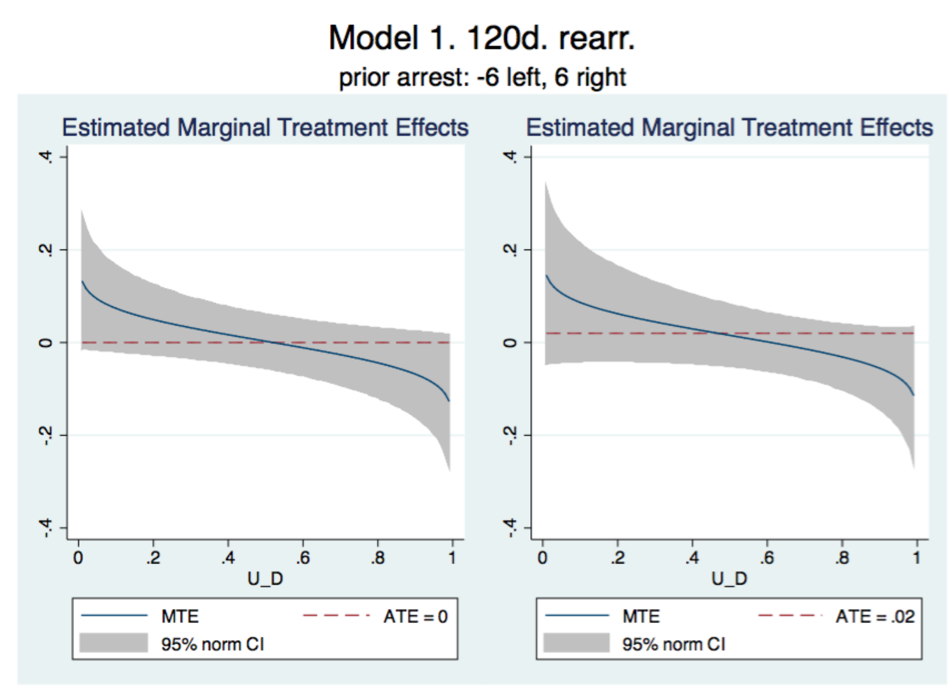


Figure 39. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 120-day threshold, outcome model #1, relative arrest = -4 and relative arrest = +4.

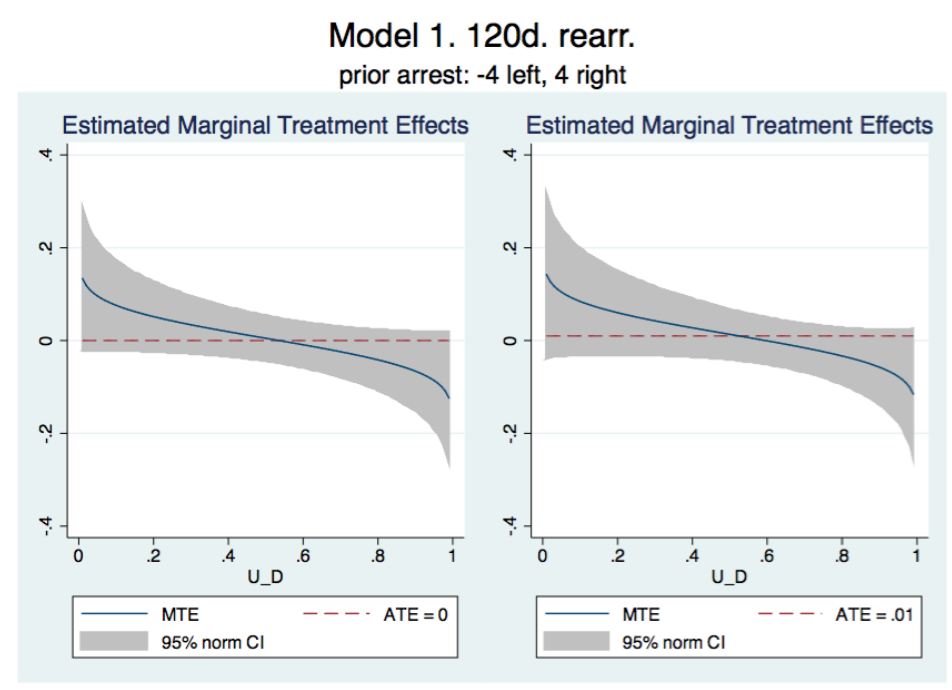


Figure 40. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 120-day threshold, outcome model #1, relative arrest = -2 and relative arrest = +2.

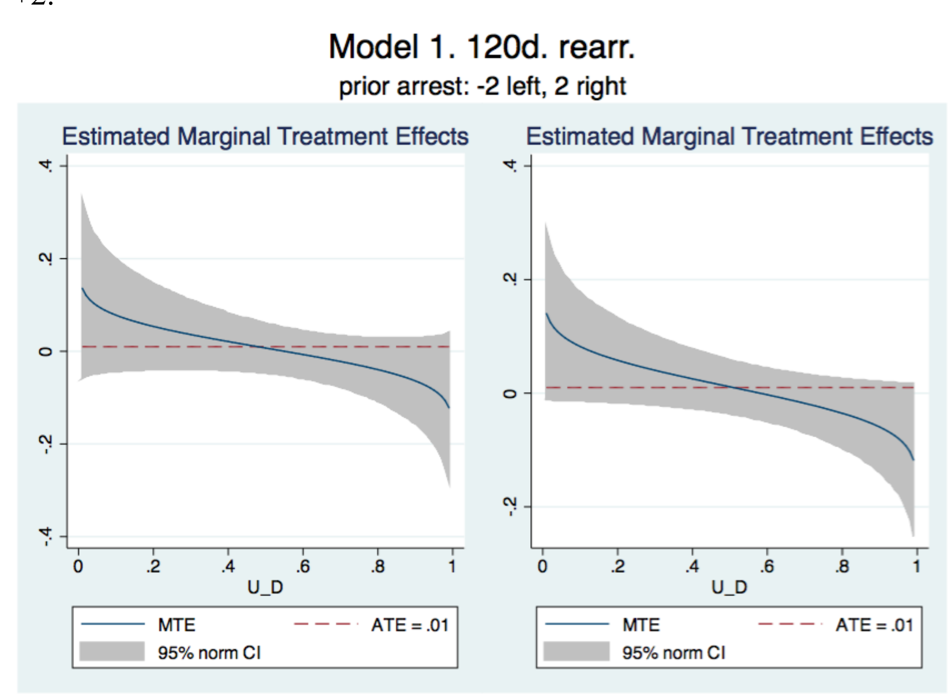


Figure 41. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 150-day threshold, outcome model #1, relative arrest = -6 and relative arrest = +6.

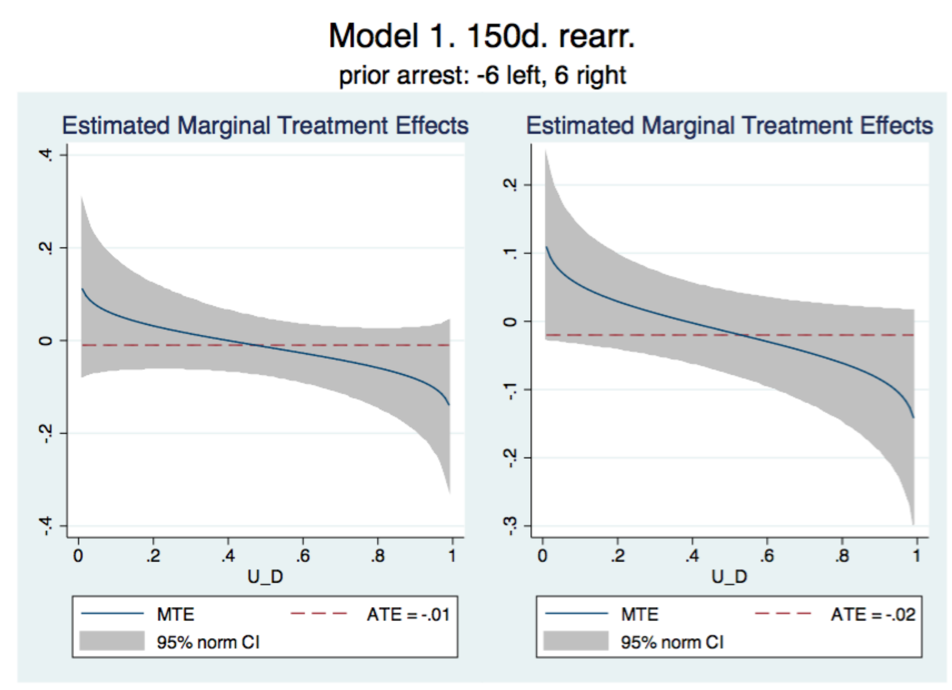


Figure 42. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 150-day threshold, outcome model #1, relative arrest = -4 and relative arrest = +4.

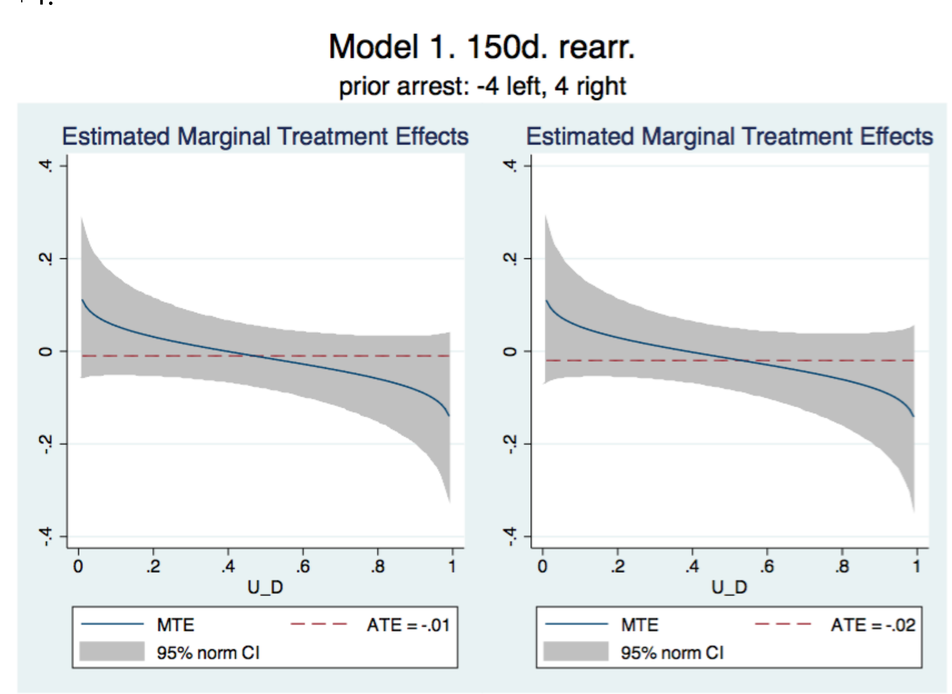


Figure 43. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 150-day threshold, outcome model #1, relative arrest = -2 and relative arrest = +2.

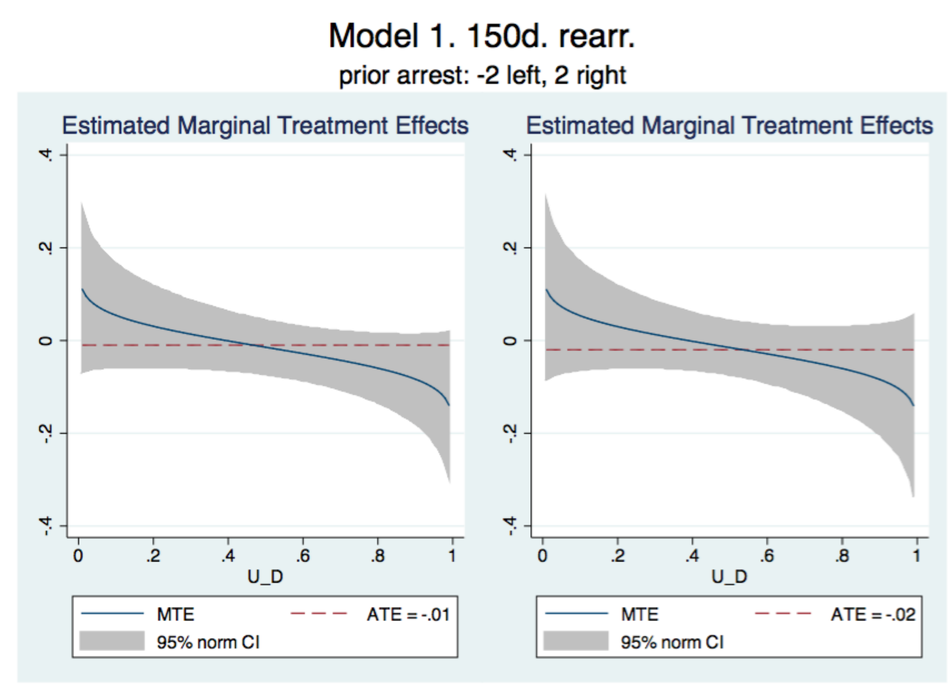


Figure 44. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 180-day threshold, outcome model #1, relative arrest = -6 and relative arrest = +6.

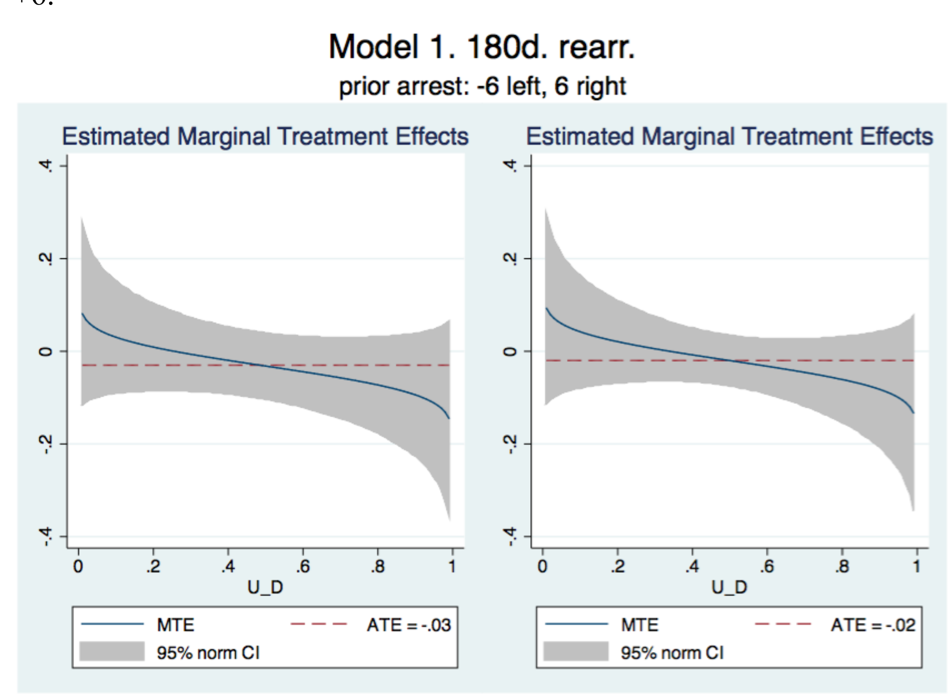


Figure 45. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 180-day threshold, outcome model #1, relative arrest = -4 and relative arrest = +4.

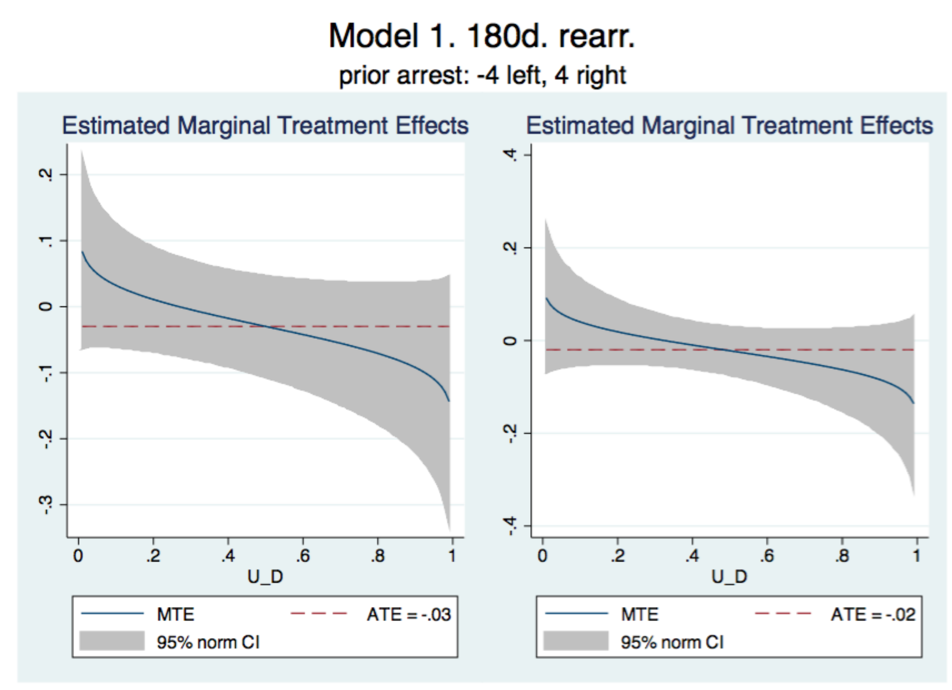


Figure 46. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 180-day threshold, outcome model #1, relative arrest = -2 and relative arrest = +2.

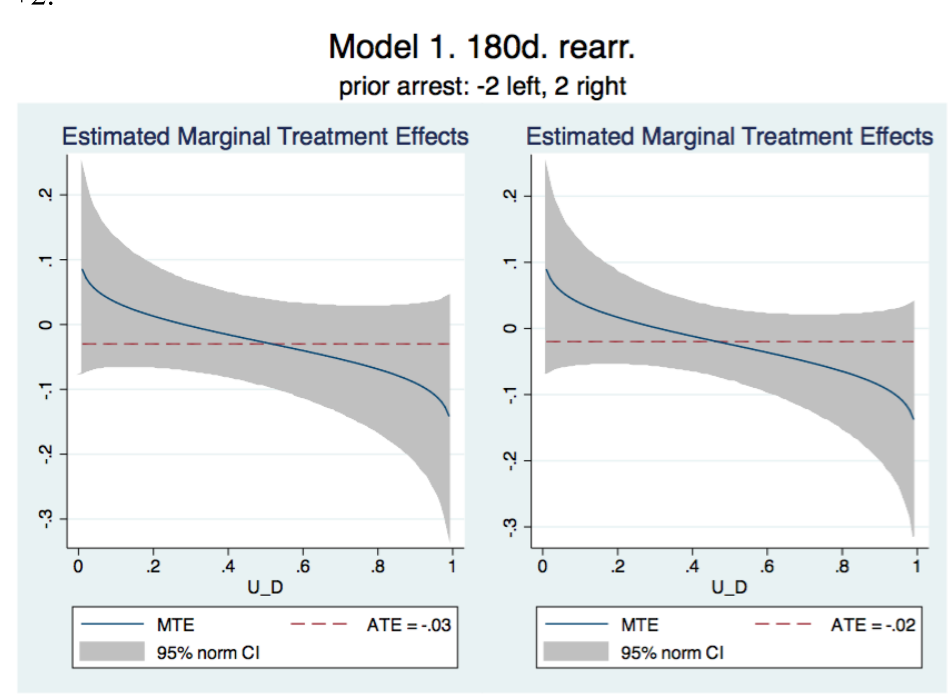


Figure 47. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 120-day threshold, outcome model #1, relative arrest = -6 and relative arrest = +6.

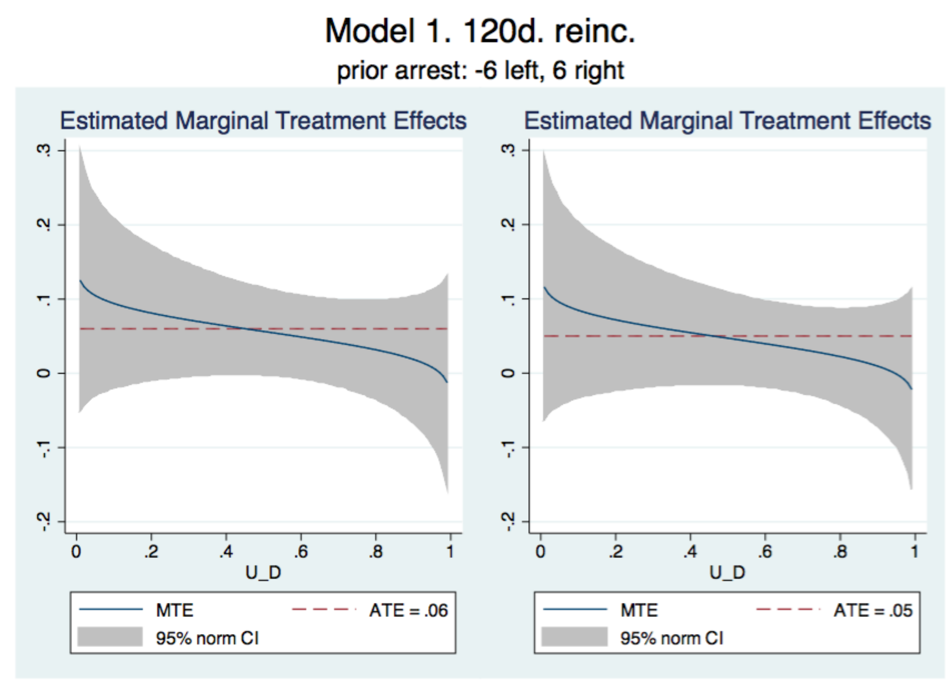


Figure 48. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 120-day threshold, outcome model #1, relative arrest = -4 and relative arrest = +4.

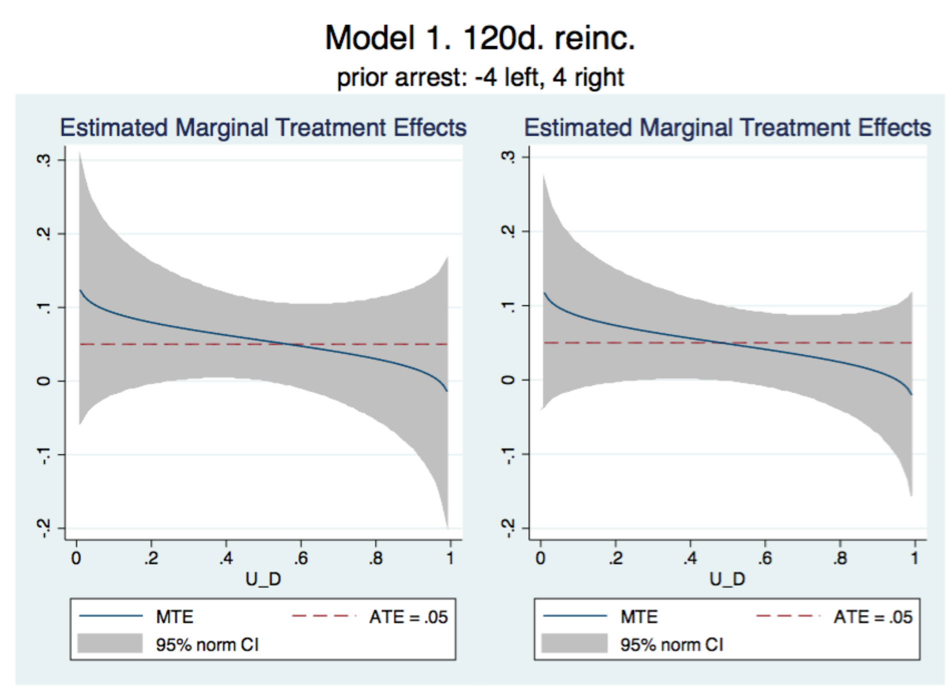


Figure 49. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 120-day threshold, outcome model #1, relative arrest = -2 and relative arrest = +2.

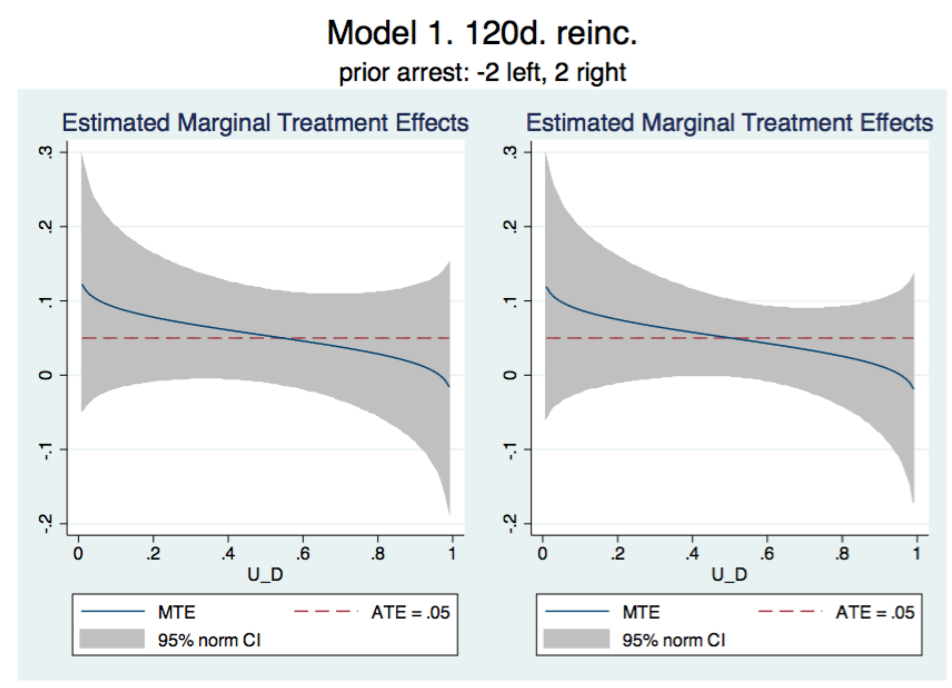


Figure 50. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 150-day threshold, outcome model #1, relative arrest = -6 and relative arrest = +6.

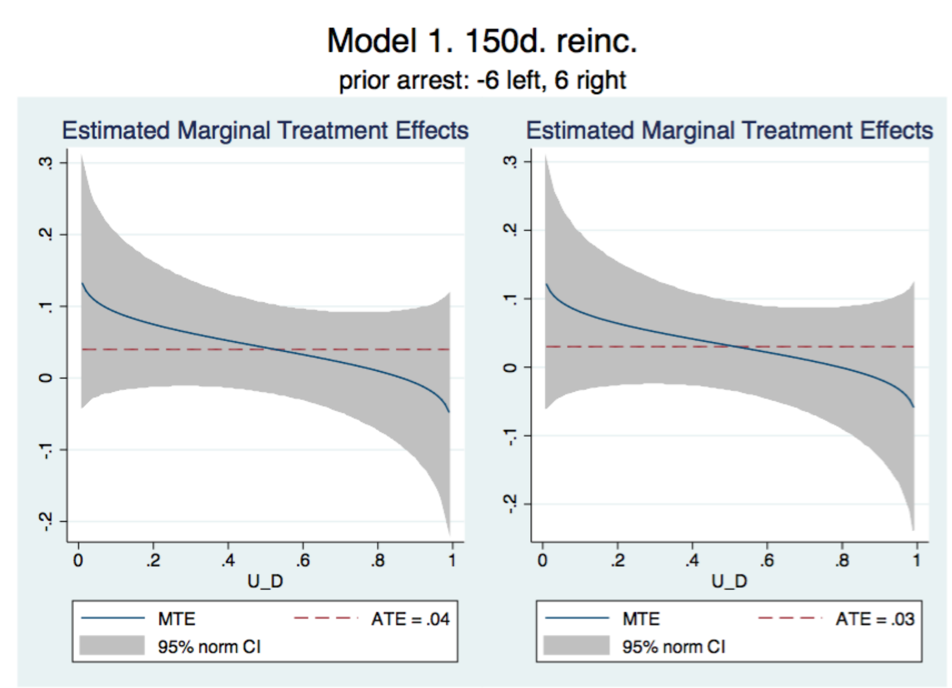


Figure 51. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 150-day threshold, outcome model #1, relative arrest = -4 and relative arrest = +4.

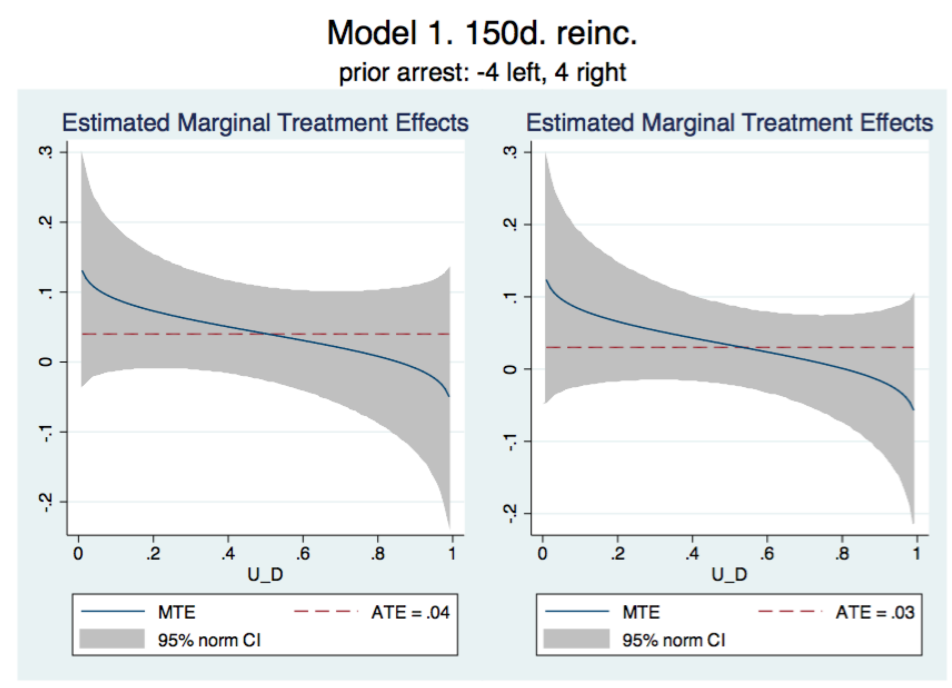


Figure 52. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 150-day threshold, outcome model #1, relative arrest = -2 and relative arrest = +2.

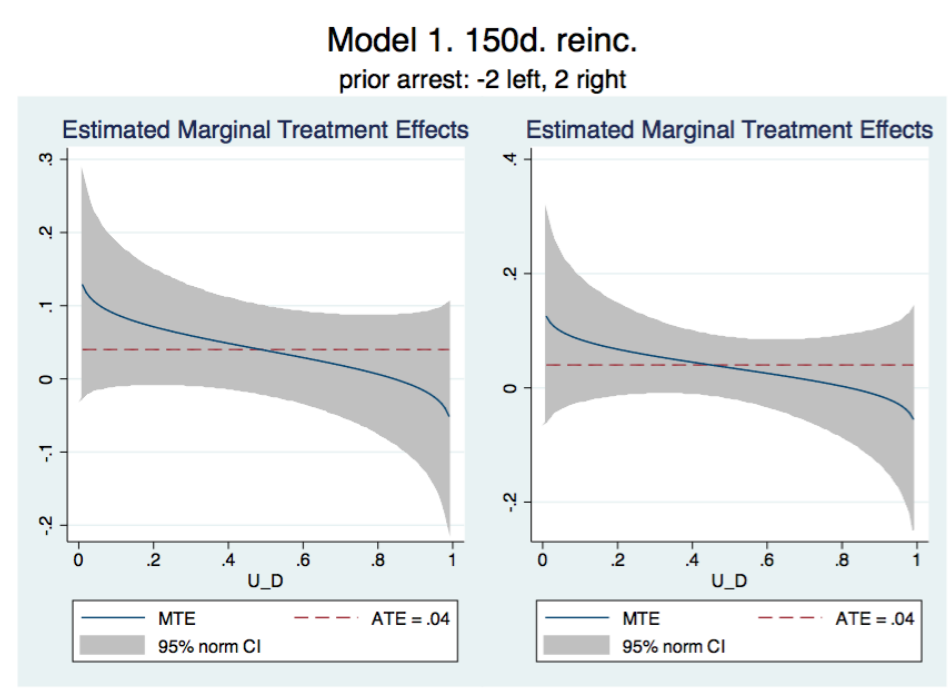


Figure 53. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 180-day threshold, outcome model #1, relative arrest = -6 and relative arrest = +6.

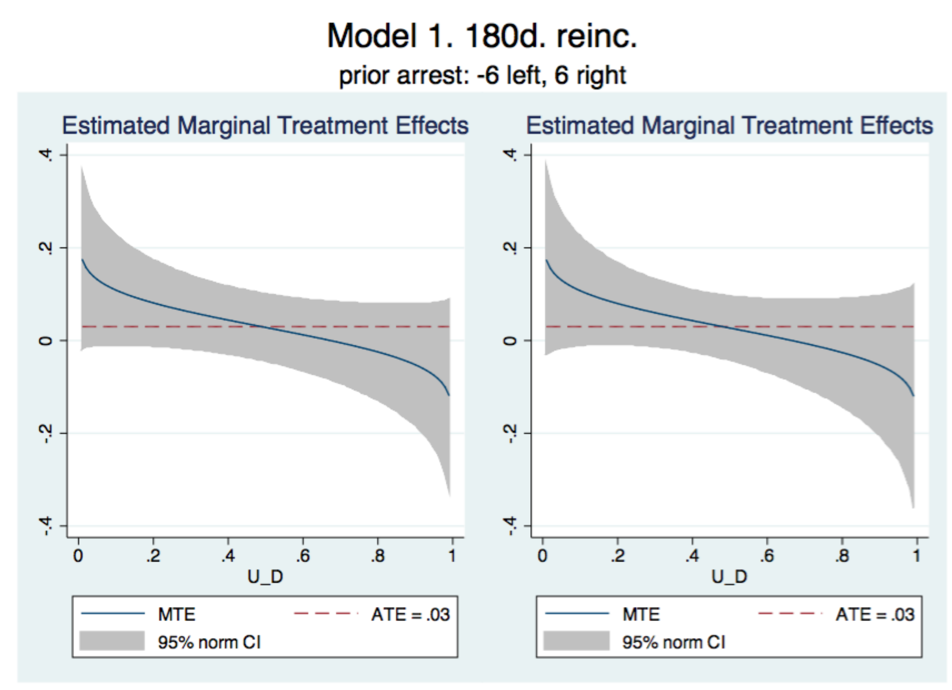


Figure 54. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 180-day threshold, outcome model #1, relative arrest = -4 and relative arrest = +4.

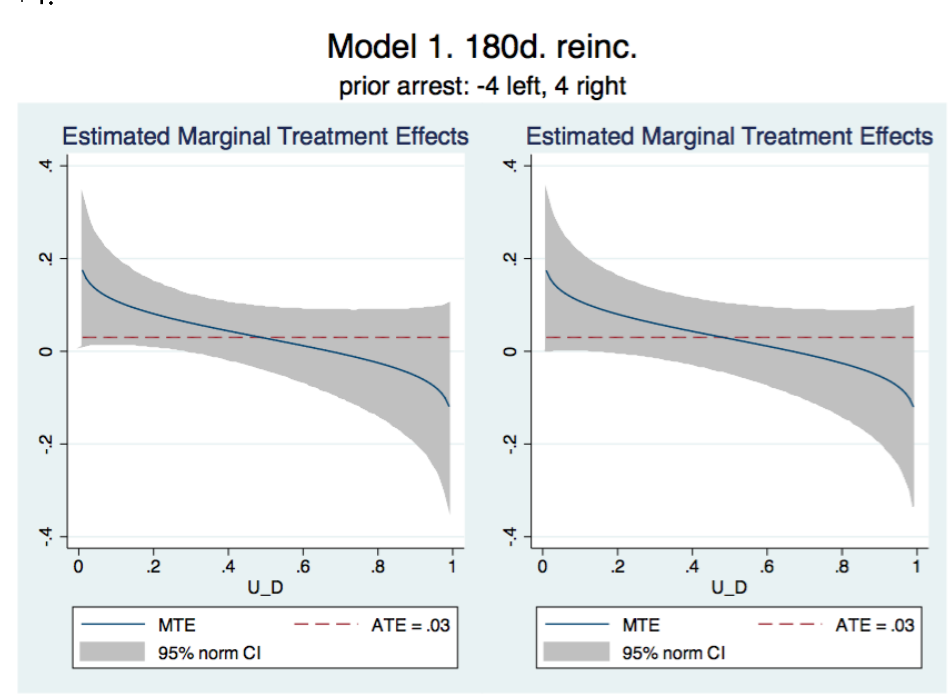
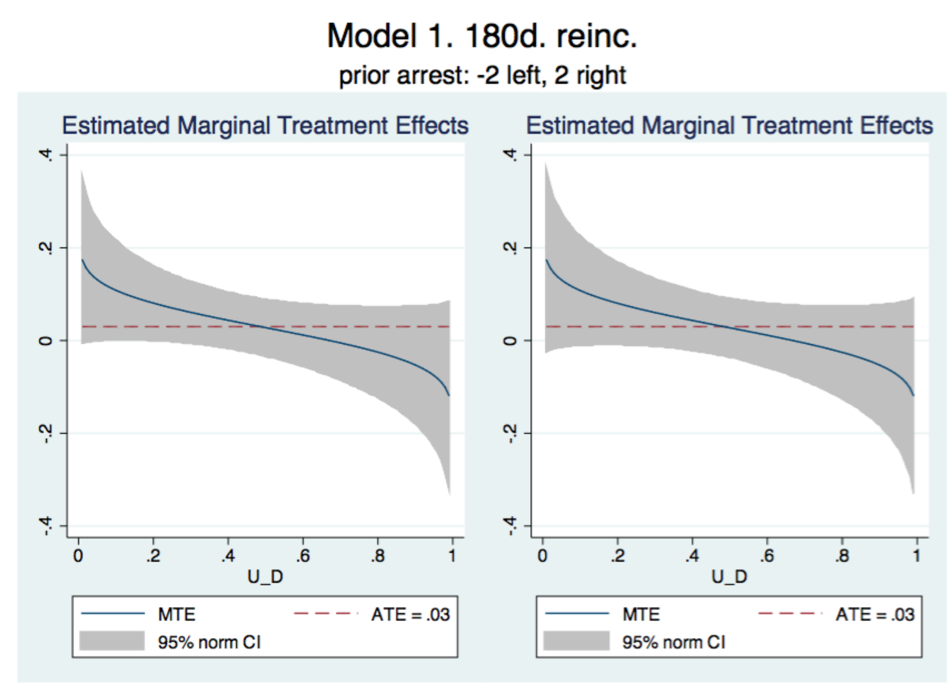


Figure 55. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 180-day threshold, outcome model #1, relative arrest = -2 and relative arrest = +2.



Average and marginal prison peer effect graphs for prior arrest in outcome model #2.

Figure 56. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 120-day threshold, outcome model #2, relative arrest = -6 and relative arrest = +6.

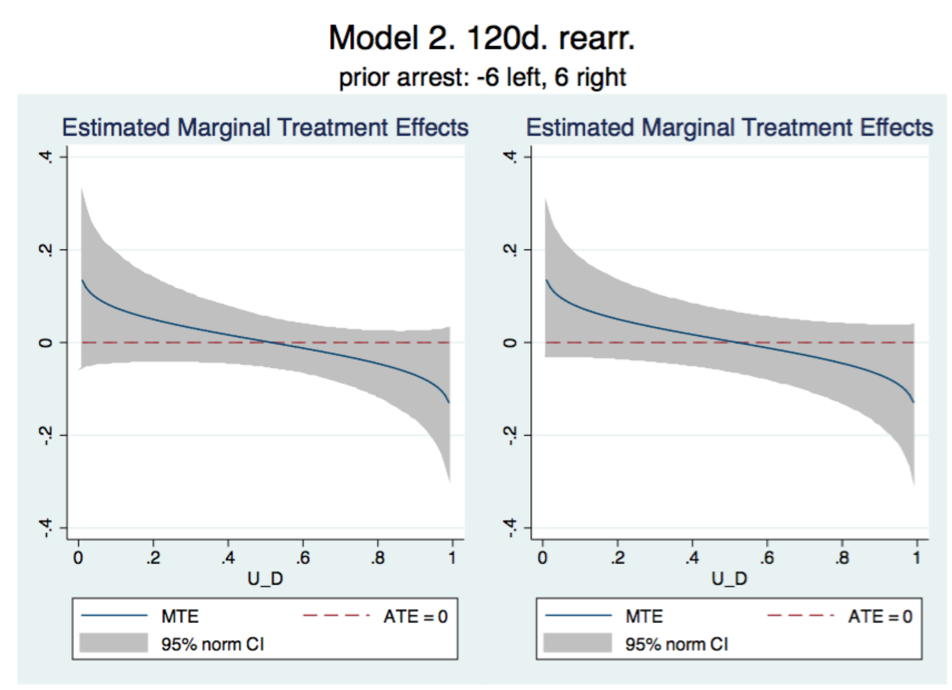


Figure 57. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 120-day threshold, outcome model #2, relative arrest = -4 and relative arrest = +4.

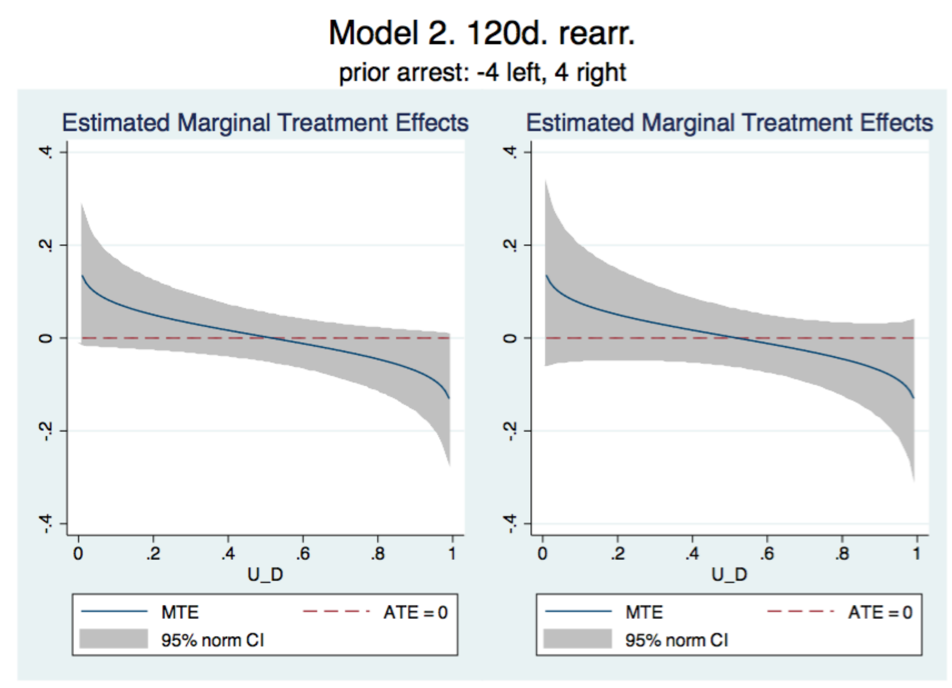


Figure 58. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 120-day threshold, outcome model #2, relative arrest = -2 and relative arrest = +2.

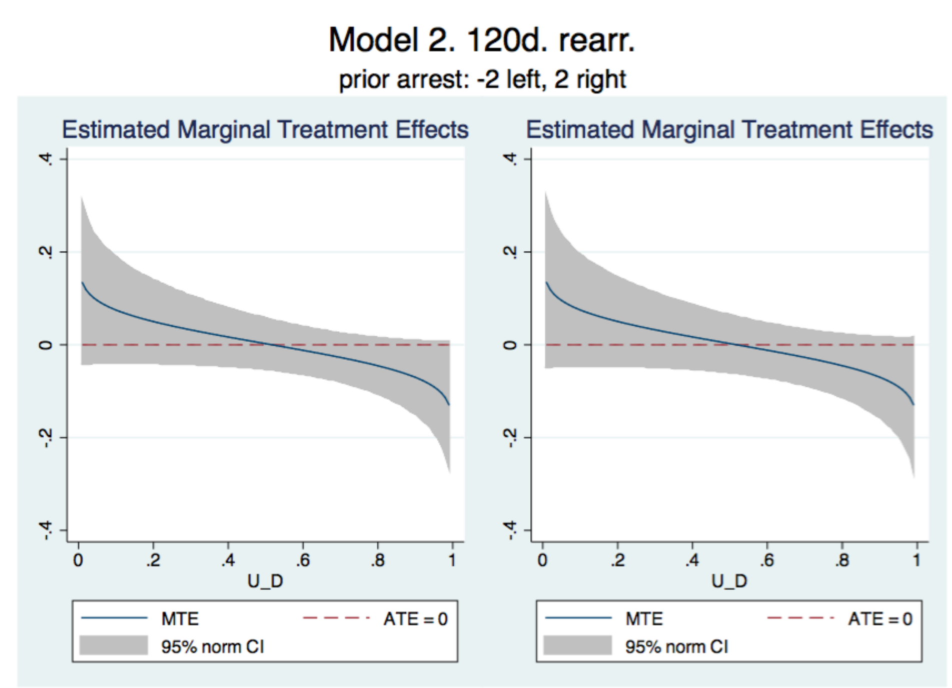


Figure 59. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 150-day threshold, outcome model #2, relative arrest = -6 and relative arrest = +6.

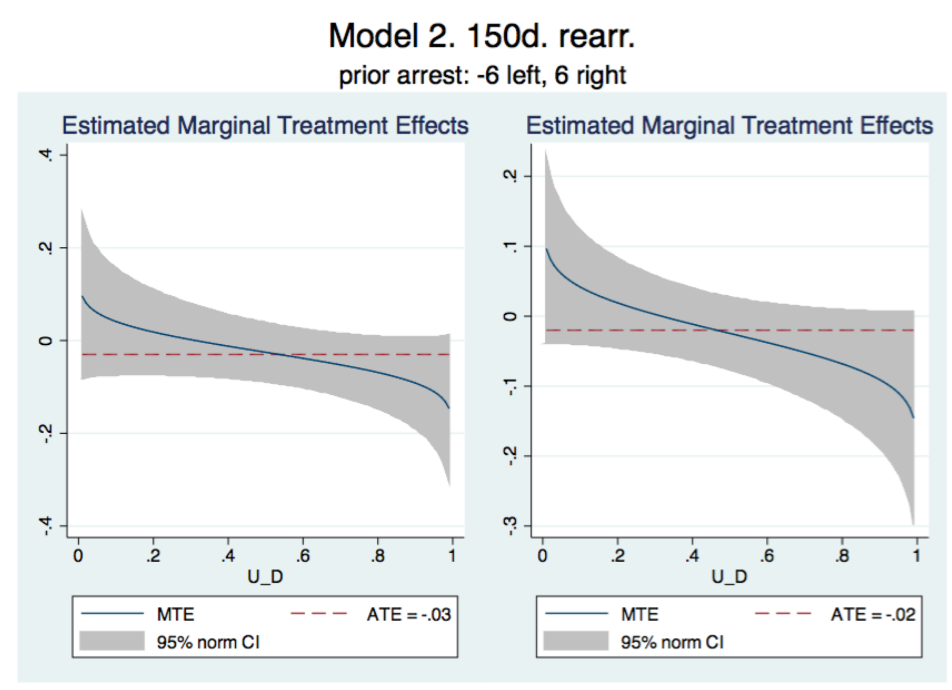


Figure 60. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 150-day threshold, outcome model #2, relative arrest = -4 and relative arrest = +4.

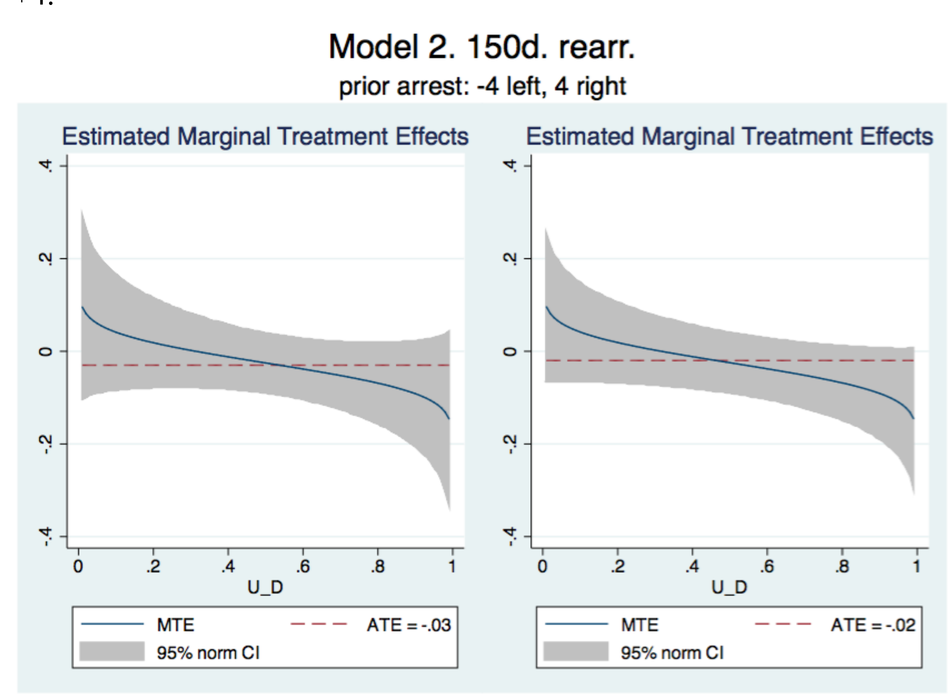


Figure 61. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 150-day threshold, outcome model #2, relative arrest = -2 and relative arrest = +2.

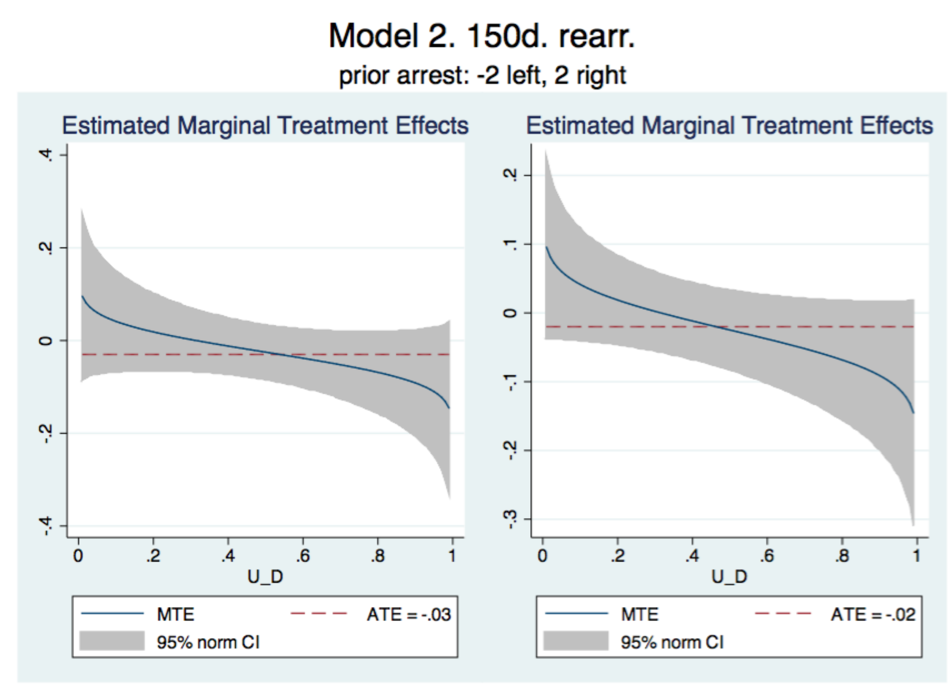


Figure 62. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 180-day threshold, outcome model #2, relative arrest = -6 and relative arrest = +6.

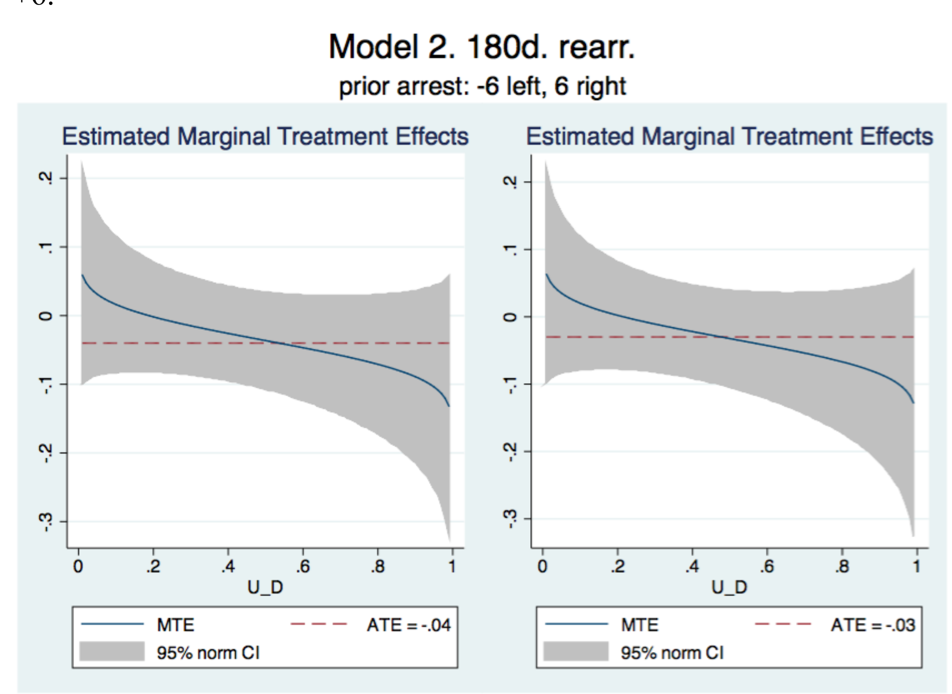


Figure 63. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 180-day threshold, outcome model #2, relative arrest = -4 and relative arrest = +4.

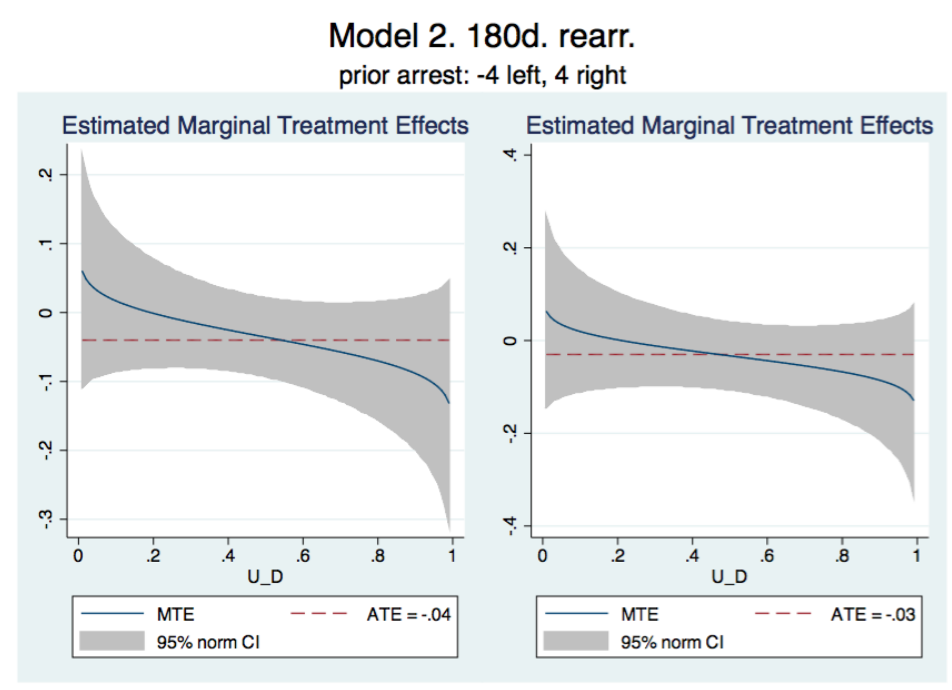


Figure 64. Average and marginal prison peer effects of relative prior arrest on releasees' rearrest at the 180-day threshold, outcome model #2, relative arrest = -2 and relative arrest = +2.

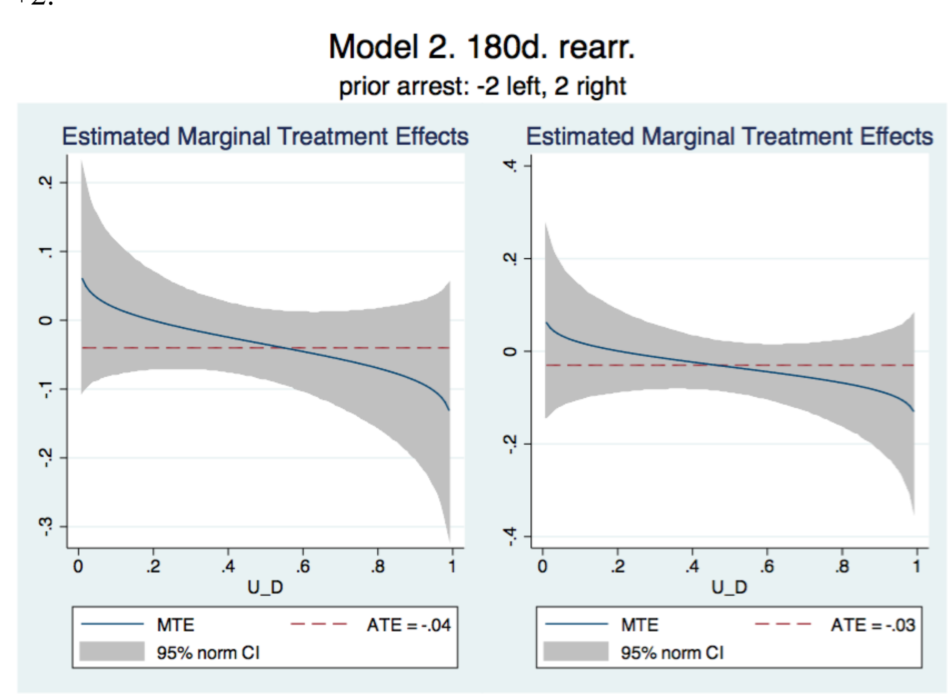


Figure 65. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 120-day threshold, outcome model #2, relative arrest = -6 and relative arrest = +6.

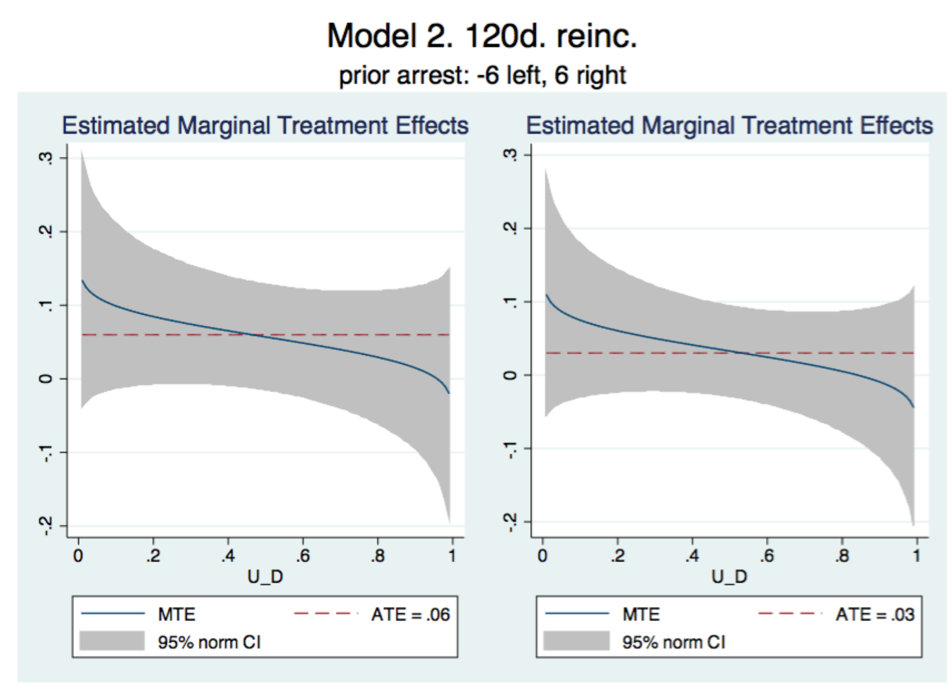


Figure 66. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 120-day threshold, outcome model #2, relative arrest = -4 and relative arrest = +4.

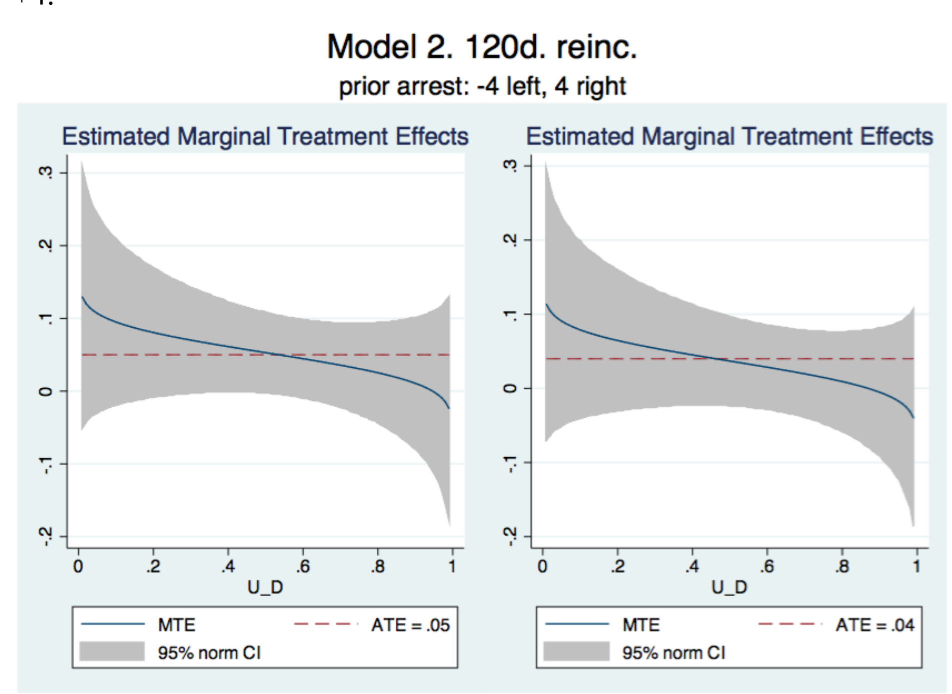


Figure 67. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 120-day threshold, outcome model #2, relative arrest = -2 and relative arrest = +2.

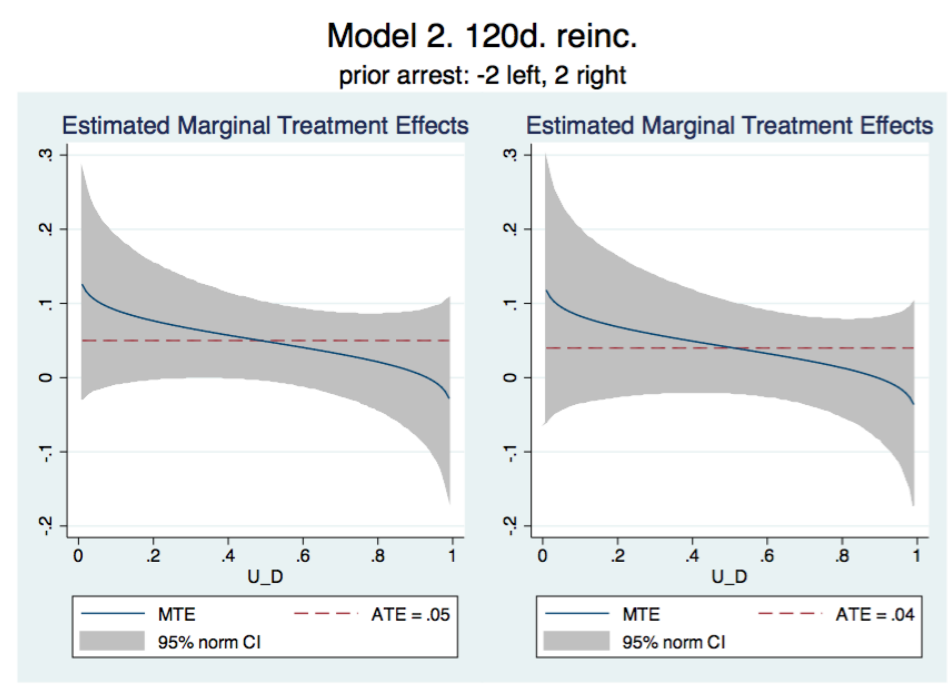


Figure 68. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 150-day threshold, outcome model #2, relative arrest = -6 and relative arrest = +6.

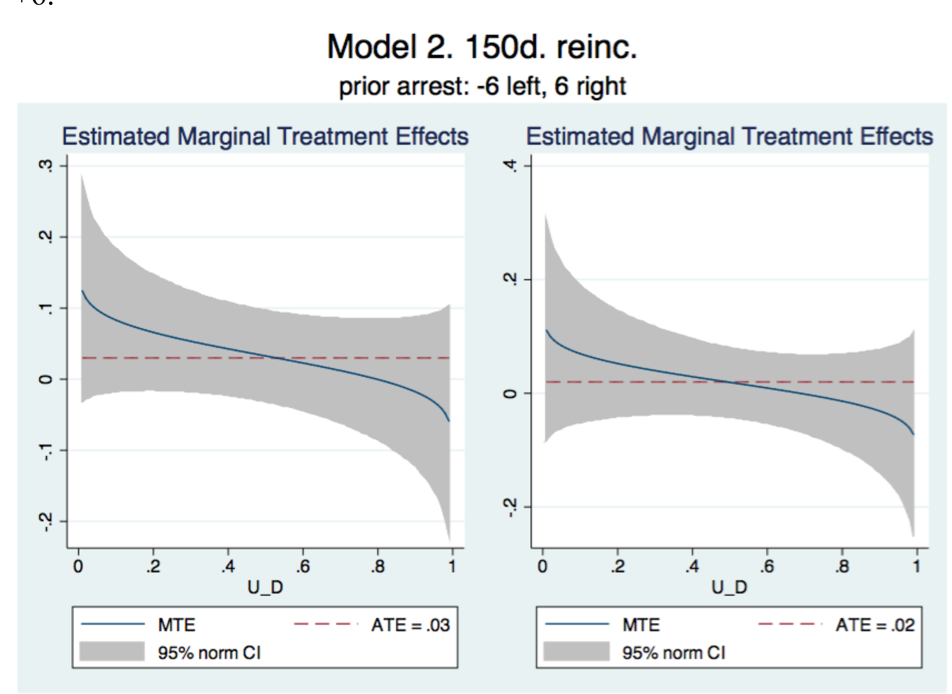


Figure 69. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 150-day threshold, outcome model #2, relative arrest = -4 and relative arrest = +4.

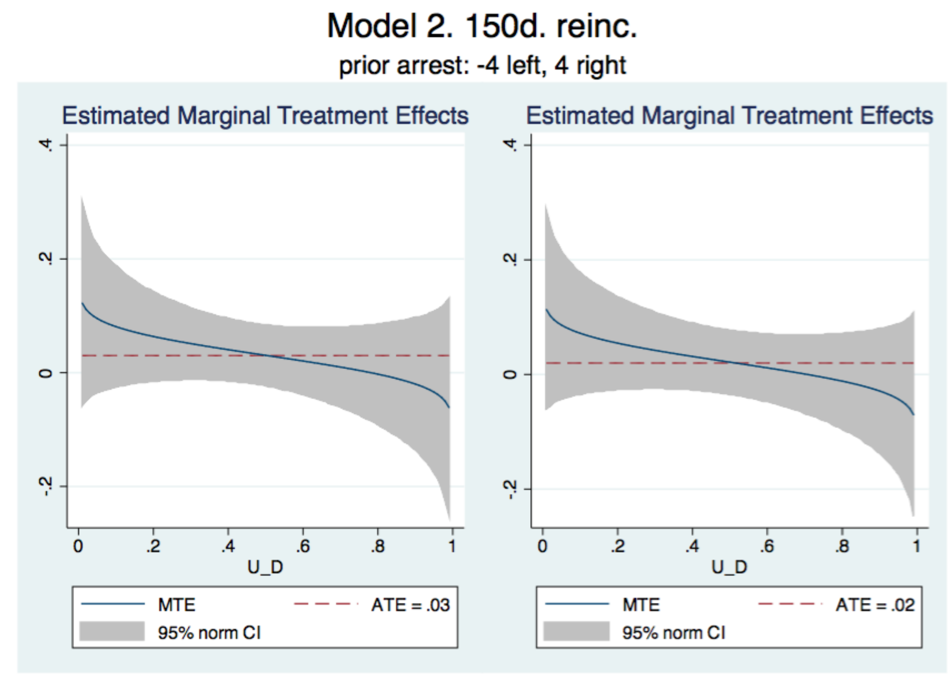


Figure 70. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 150-day threshold, outcome model #2, relative arrest = -2 and relative arrest = +2.

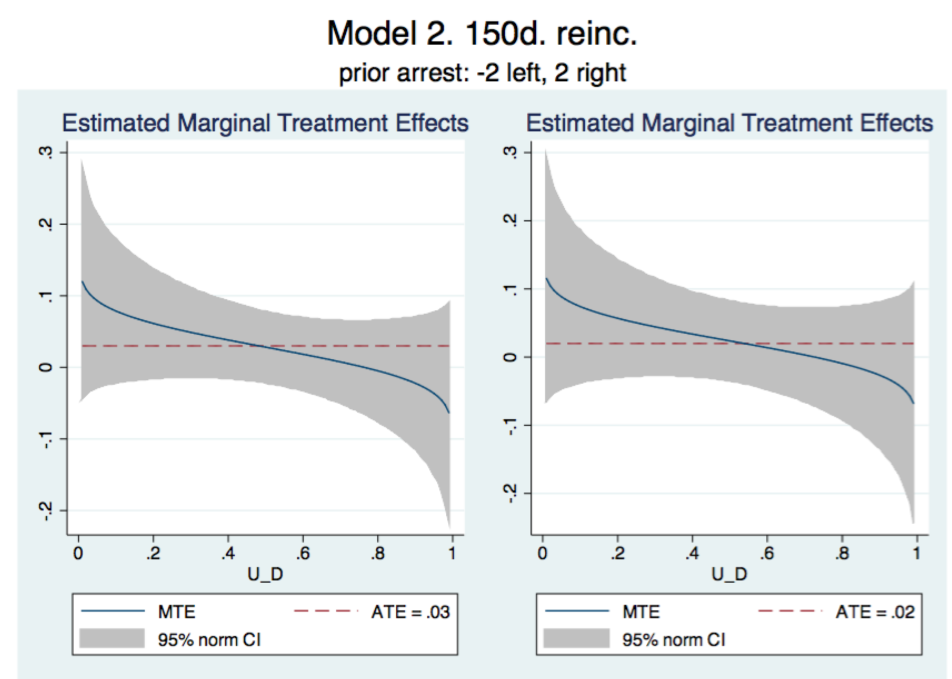


Figure 71. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 180-day threshold, outcome model #2, relative arrest = -6 and relative arrest = +6.

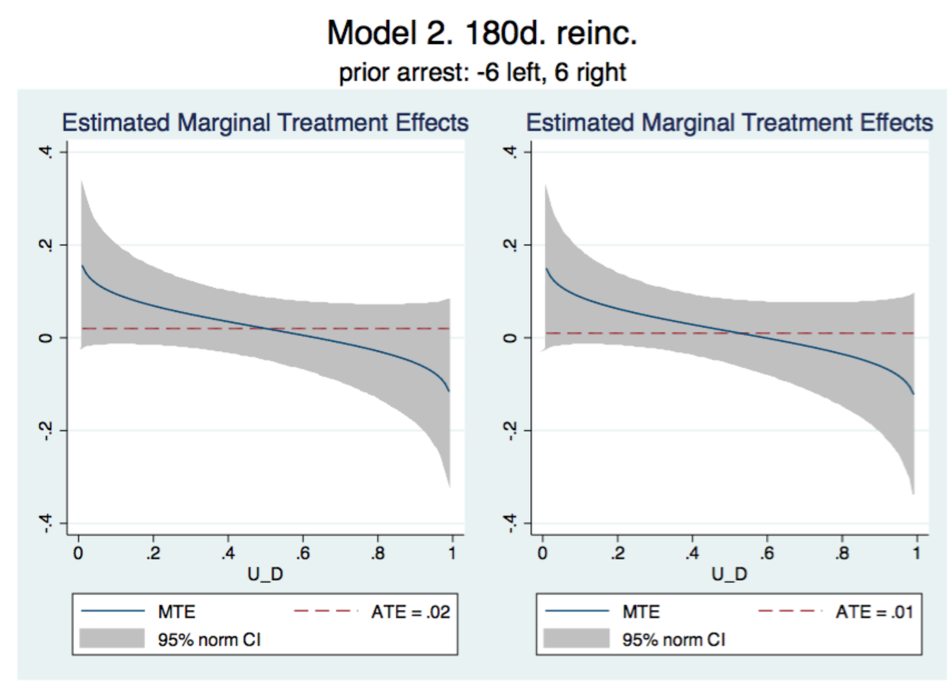


Figure 72. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 180-day threshold, outcome model #2, relative arrest = -4 and relative arrest = +4.

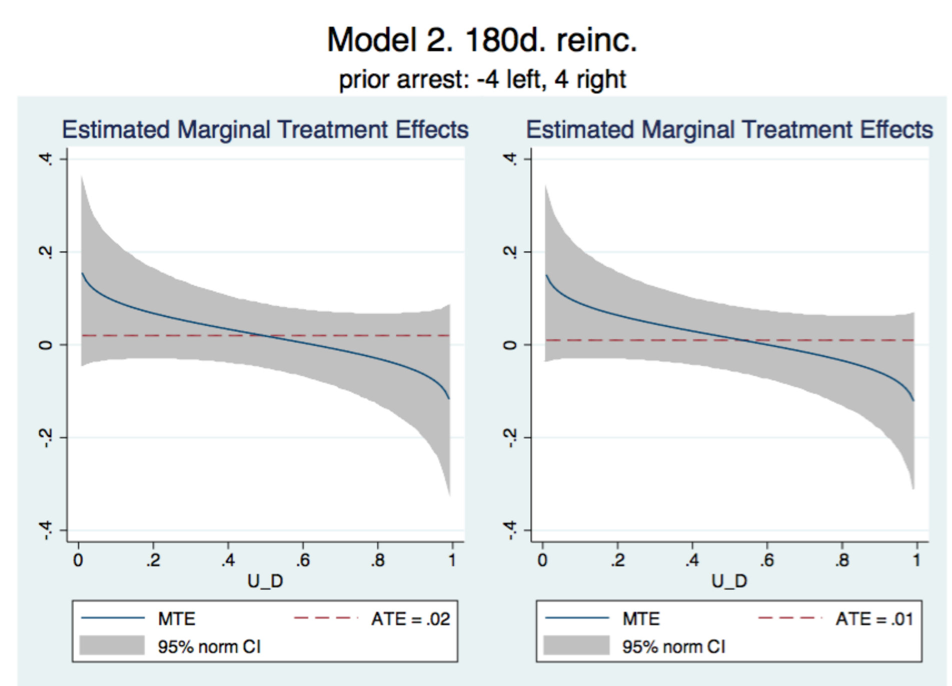
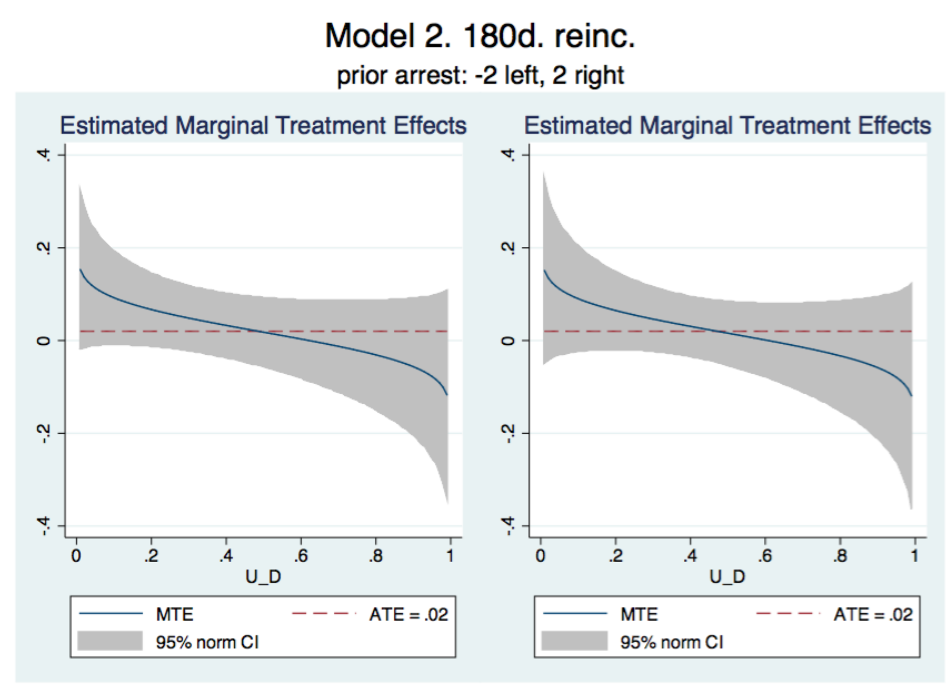


Figure 73. Average and marginal prison peer effects of relative prior arrest on releasees' recidivism at the 180-day threshold, outcome model #2, relative arrest = -2 and relative arrest = +2.



Average and marginal prison peer effect graphs for risk scores in outcome model #2.

Figure 74. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 120-day threshold, outcome model #2, relative RST = -4 and relative RST = +4.

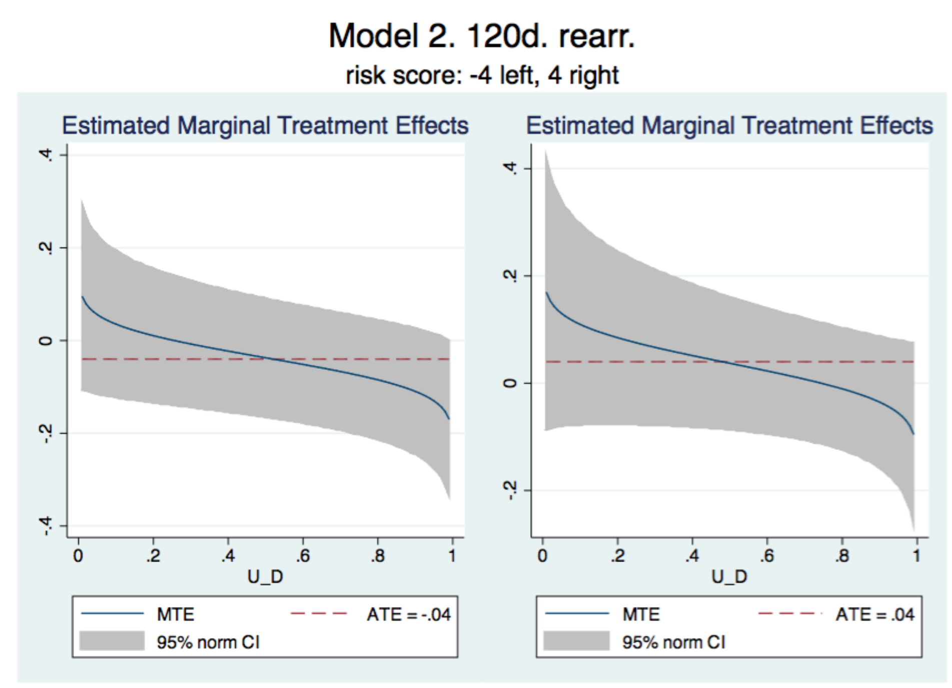


Figure 75. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 120-day threshold, outcome model #2, relative RST = -3 and relative RST = +3.

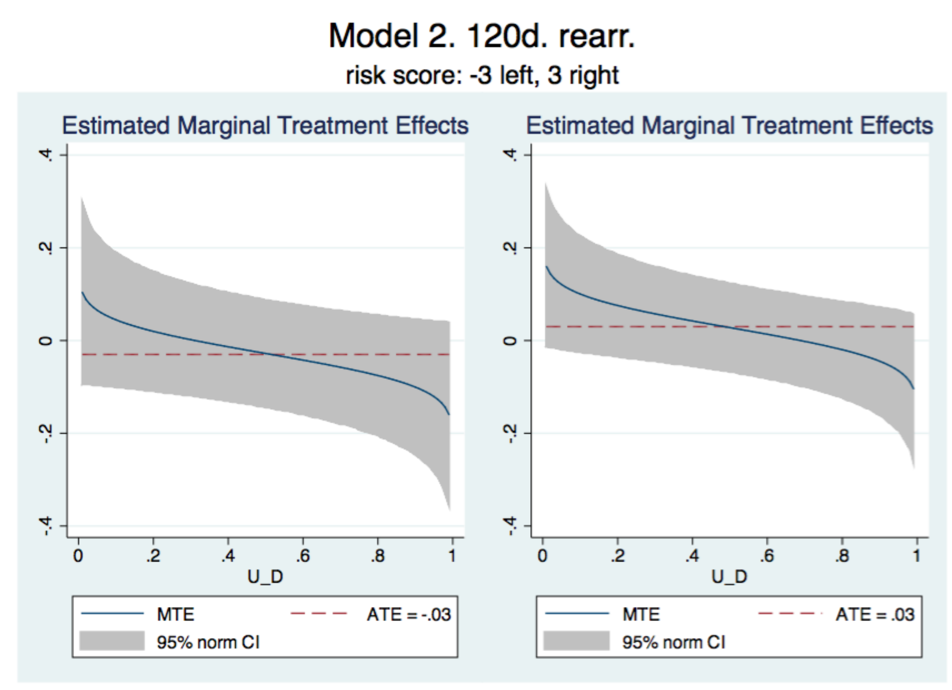


Figure 76. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 120-day threshold, outcome model #2, relative RST = -2 and relative RST = +2.

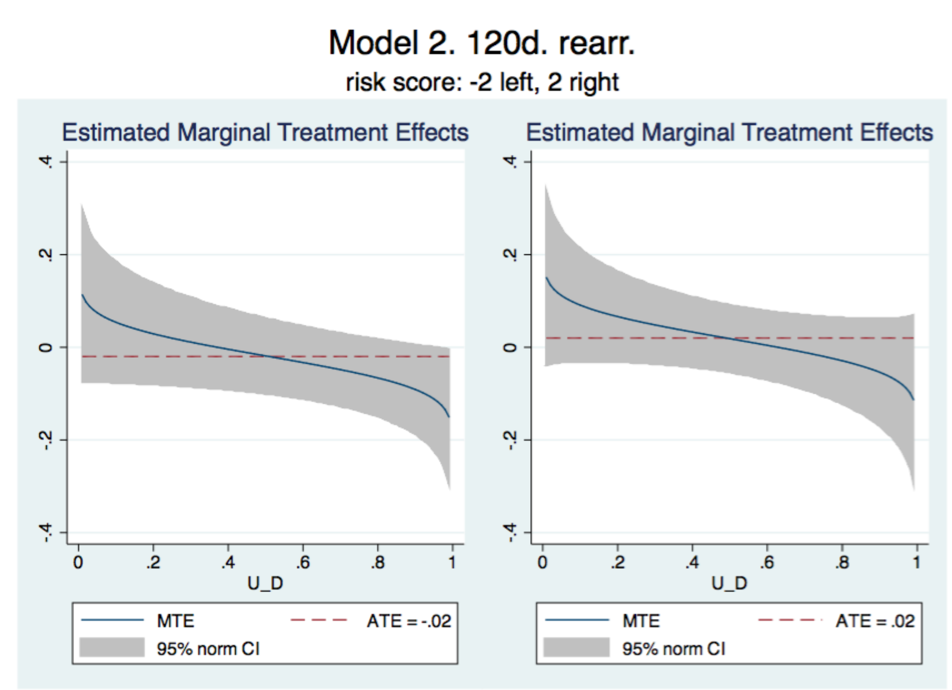


Figure 77. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 120-day threshold, outcome model #2, relative RST = -1 and relative RST = +1.

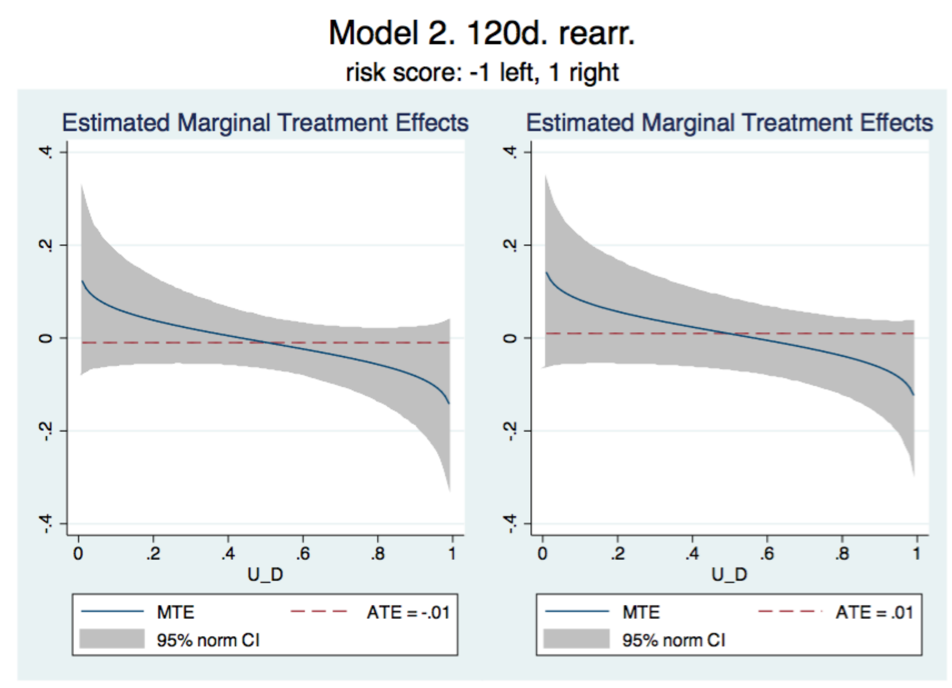


Figure 78. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 150-day threshold, outcome model #2, relative RST = -4 and relative RST = +4.

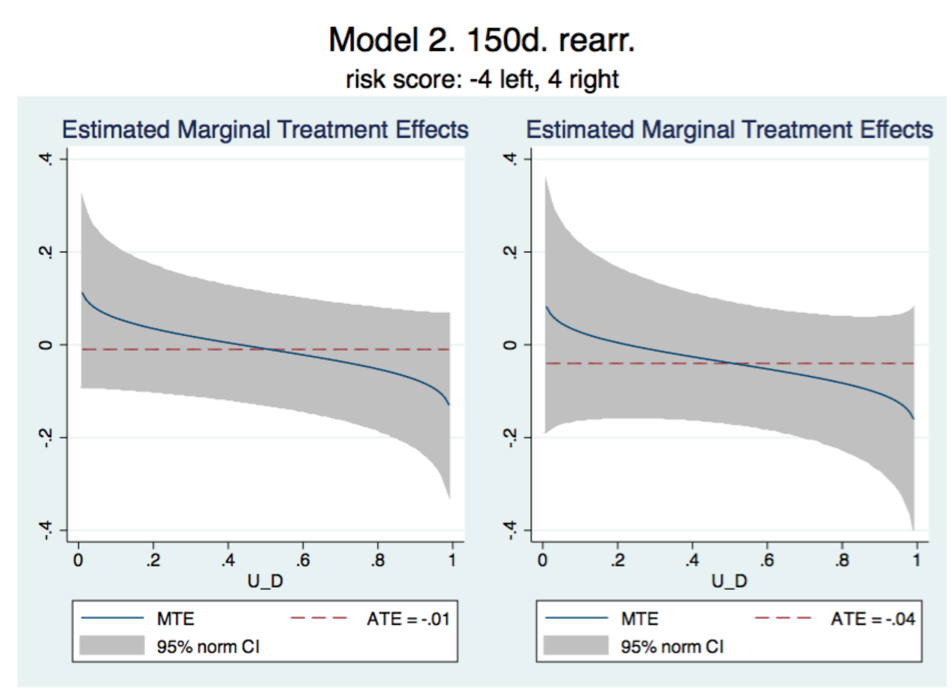


Figure 79. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 150-day threshold, outcome model #2, relative RST = -3 and relative RST = +3.

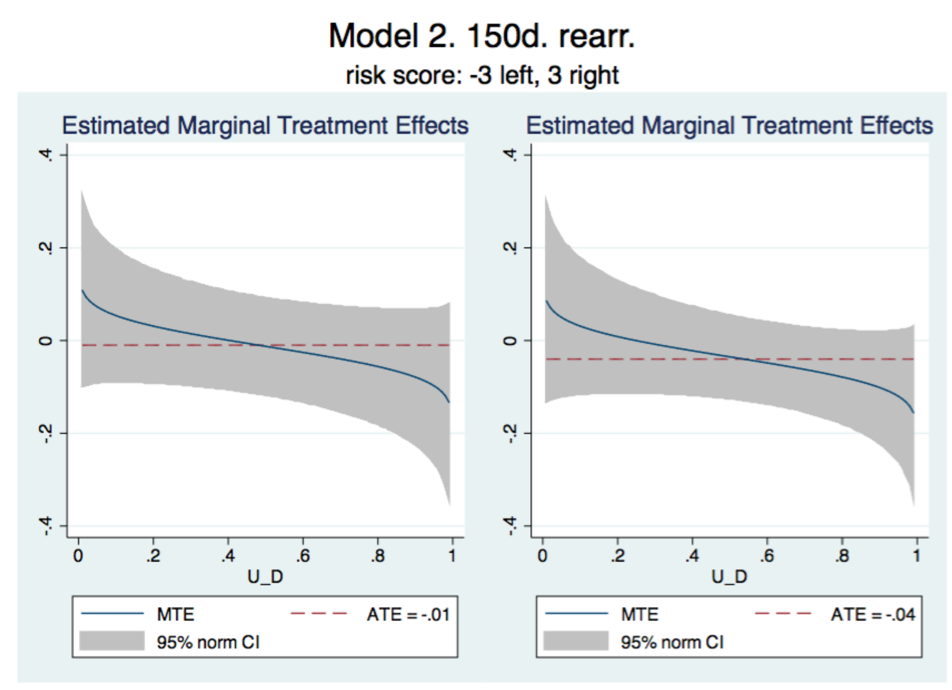


Figure 80. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 150-day threshold, outcome model #2, relative RST = -2 and relative RST = +2.

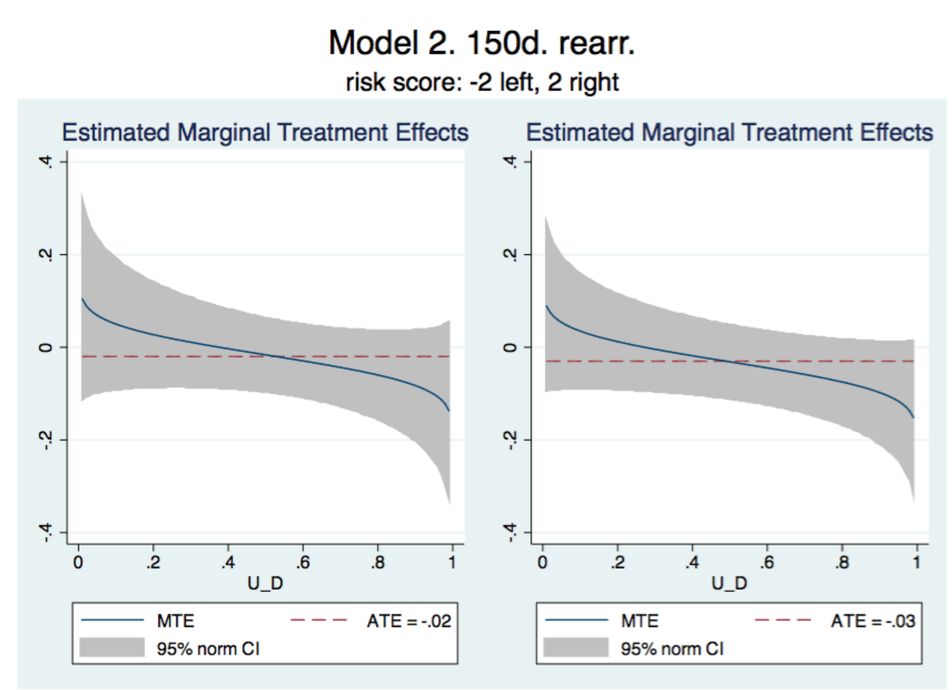


Figure 81. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 150-day threshold, outcome model #2, relative RST = -1 and relative RST = +1.

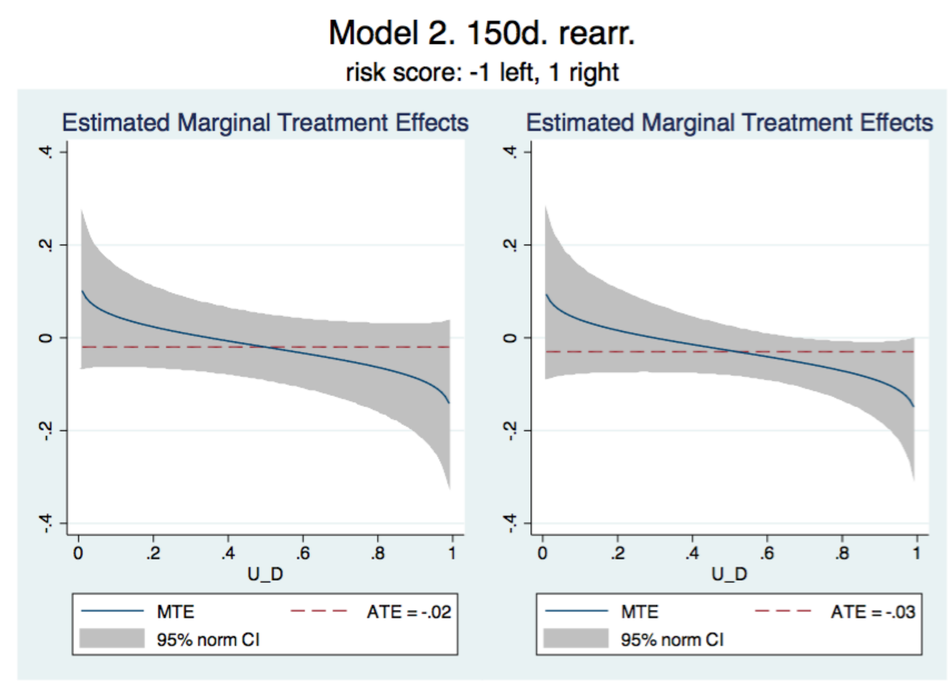


Figure 82. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 180-day threshold, outcome model #2, relative RST = -4 and relative RST = +4.

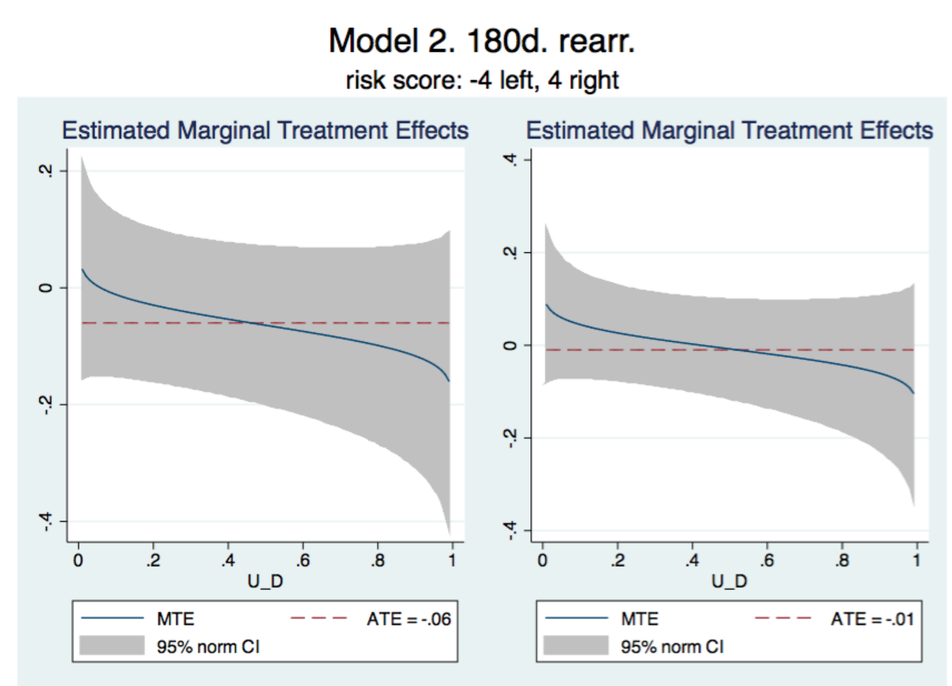


Figure 83. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 180-day threshold, outcome model #2, relative RST = -3 and relative RST = +3.

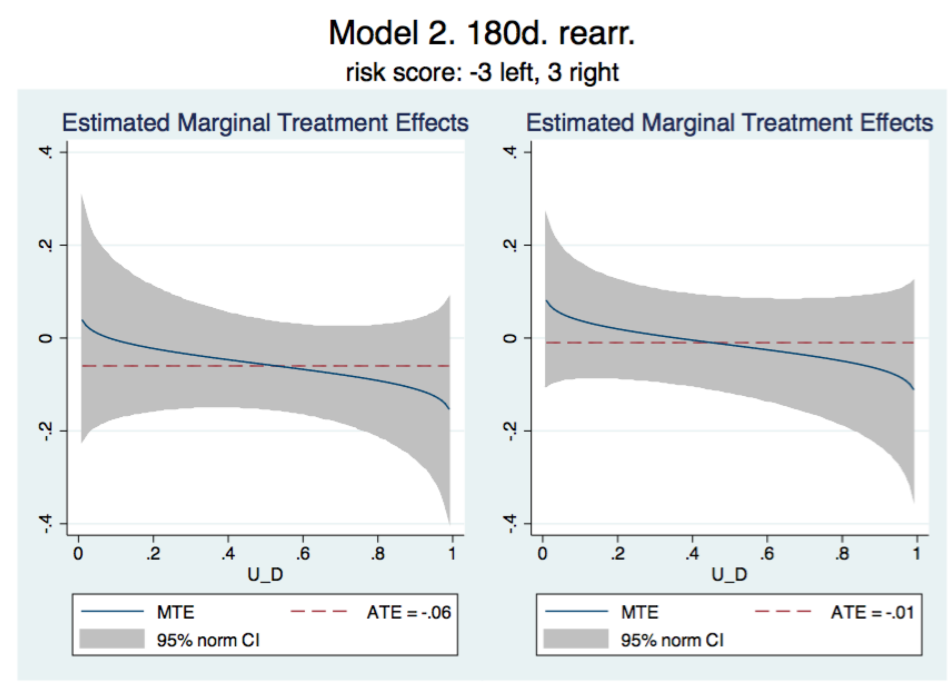


Figure 84. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 180-day threshold, outcome model #2, relative RST = -2 and relative RST = +2.

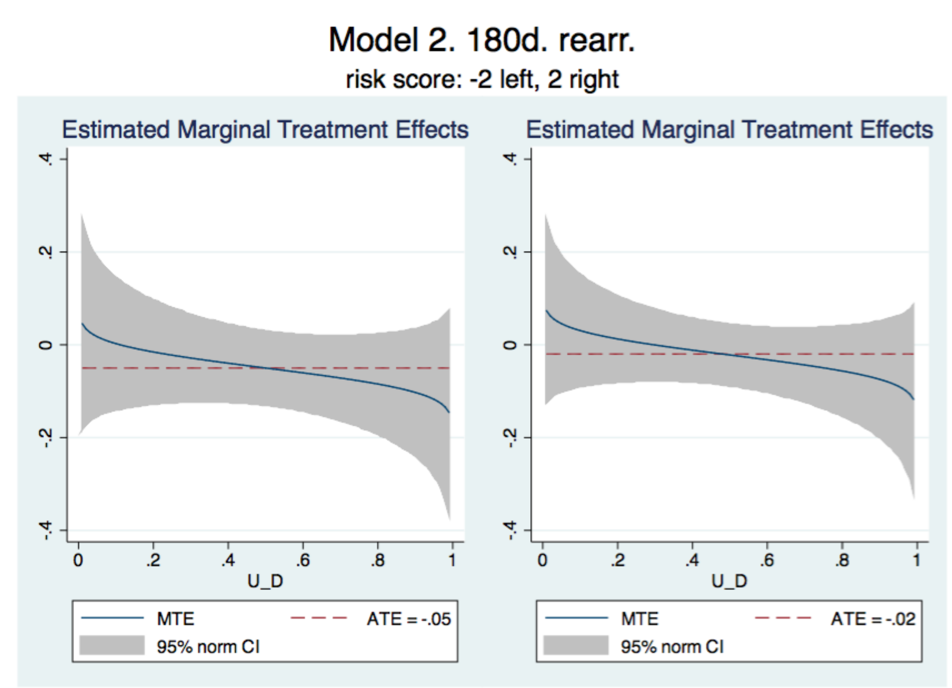


Figure 85. Average and marginal prison peer effects of relative risk score on releasees' rearrest at the 180-day threshold, outcome model #2, relative RST = -1 and relative RST = +1.

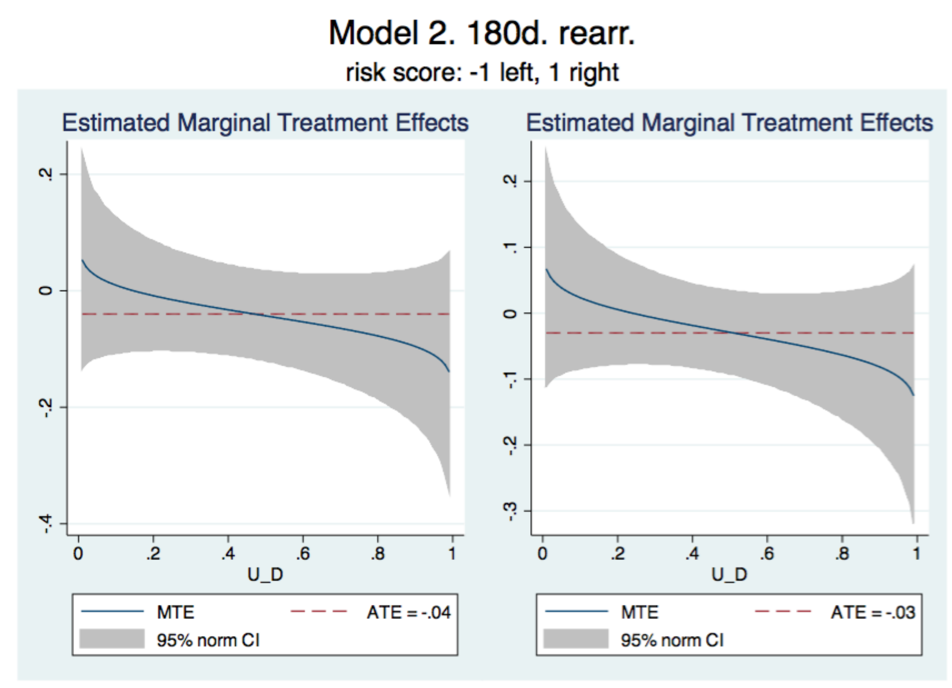


Figure 86. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 120-day threshold, outcome model #2, relative RST = -4 and relative RST = +4.

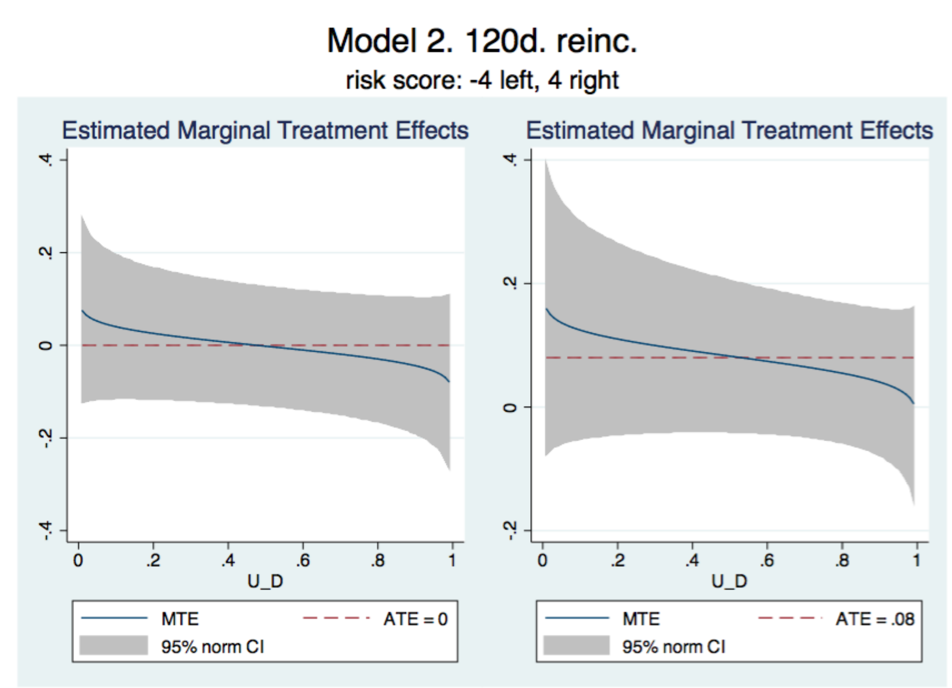


Figure 87. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 120-day threshold, outcome model #2, relative RST = -3 and relative RST = +3.

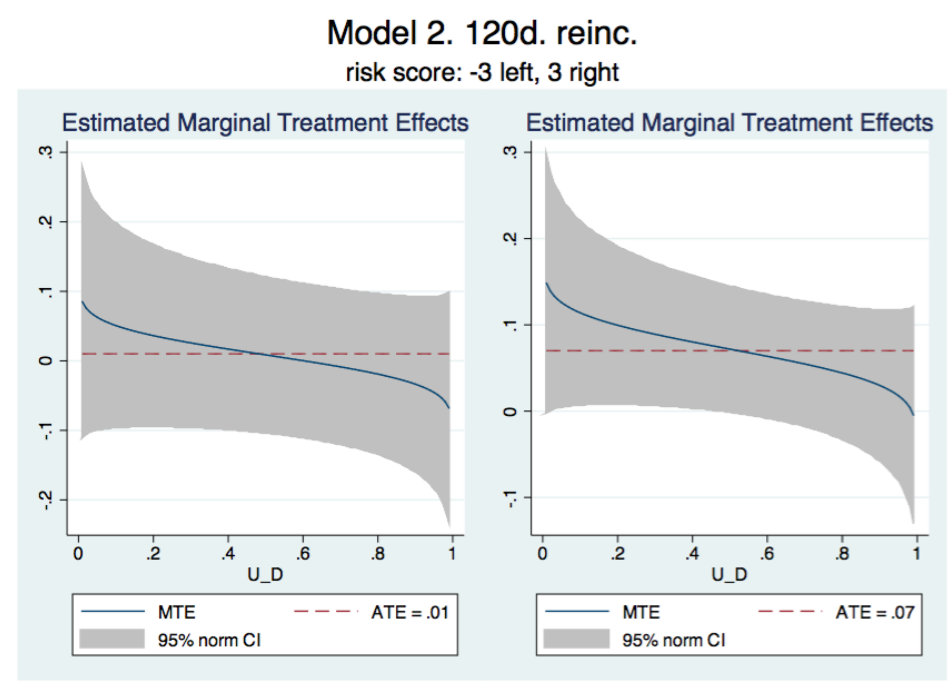


Figure 88. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 120-day threshold, outcome model #2, relative RST = -2 and relative RST = +2.

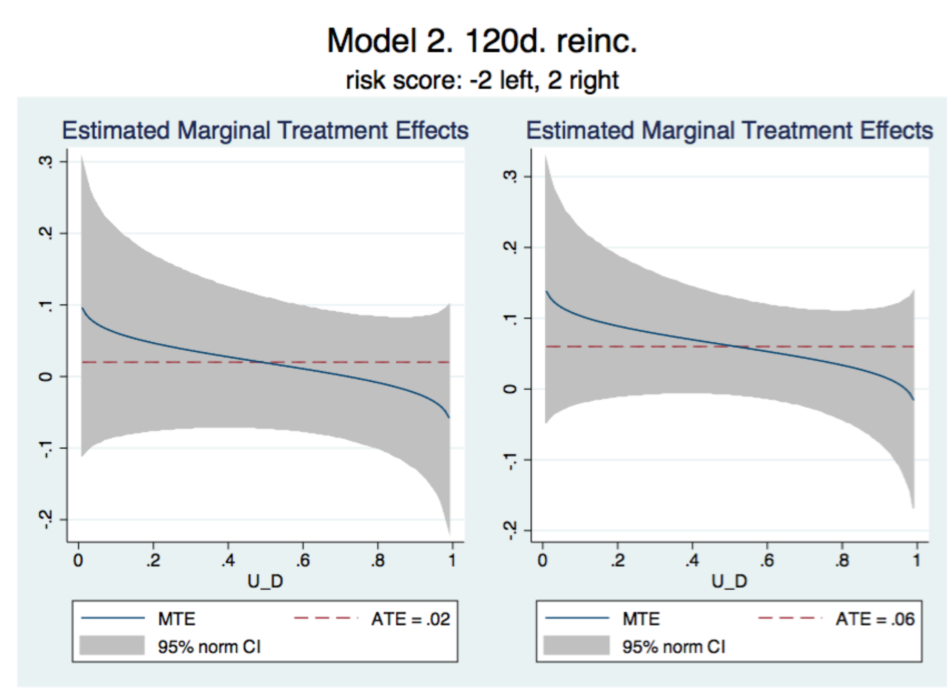


Figure 89. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 120-day threshold, outcome model #2, relative RST = -1 and relative RST = +1.

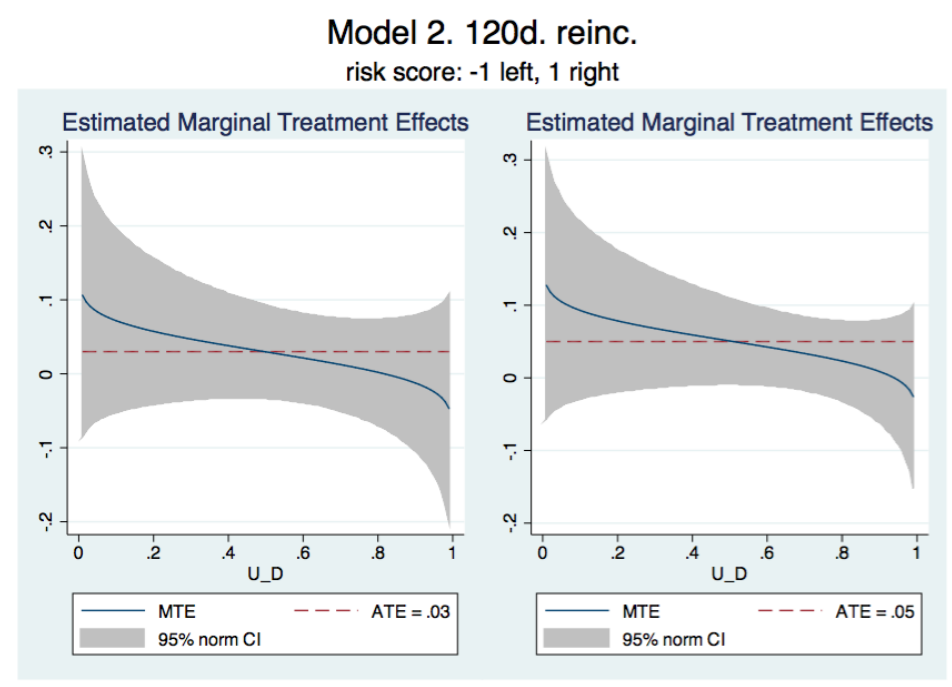


Figure 90. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 150-day threshold, outcome model #2, relative RST = -4 and relative RST = +4.

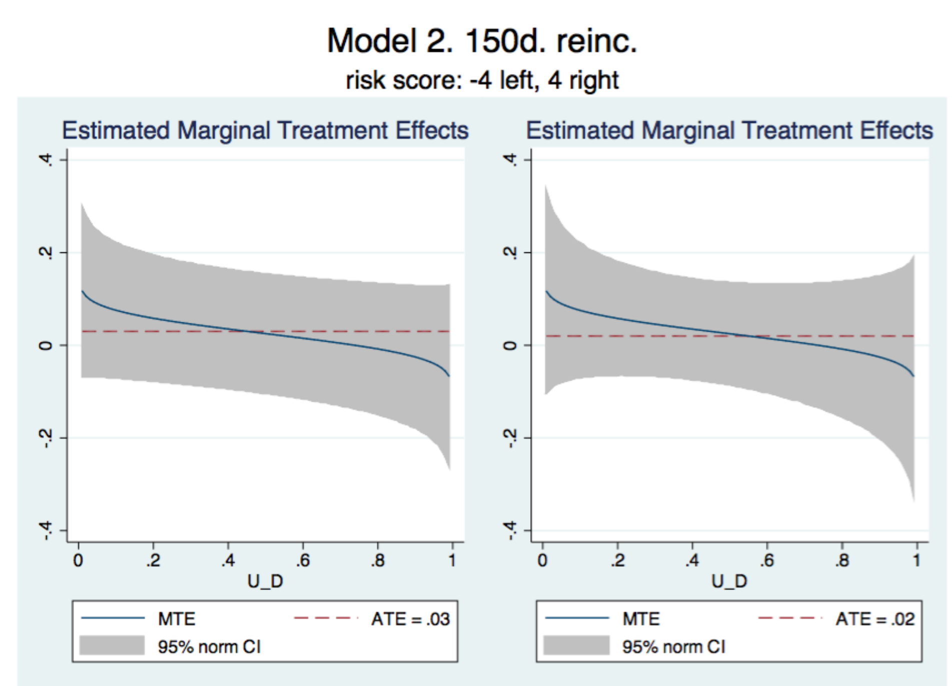


Figure 91. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 150-day threshold, outcome model #2, relative RST = -3 and relative RST = +3.

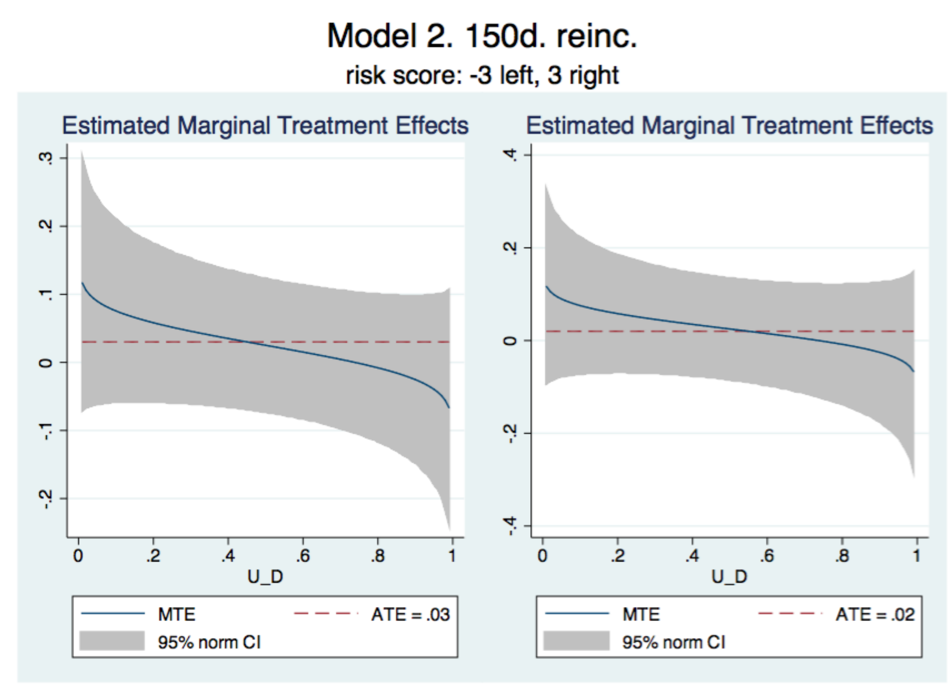


Figure 92. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 150-day threshold, outcome model #2, relative RST = -2 and RST arrest = +2.

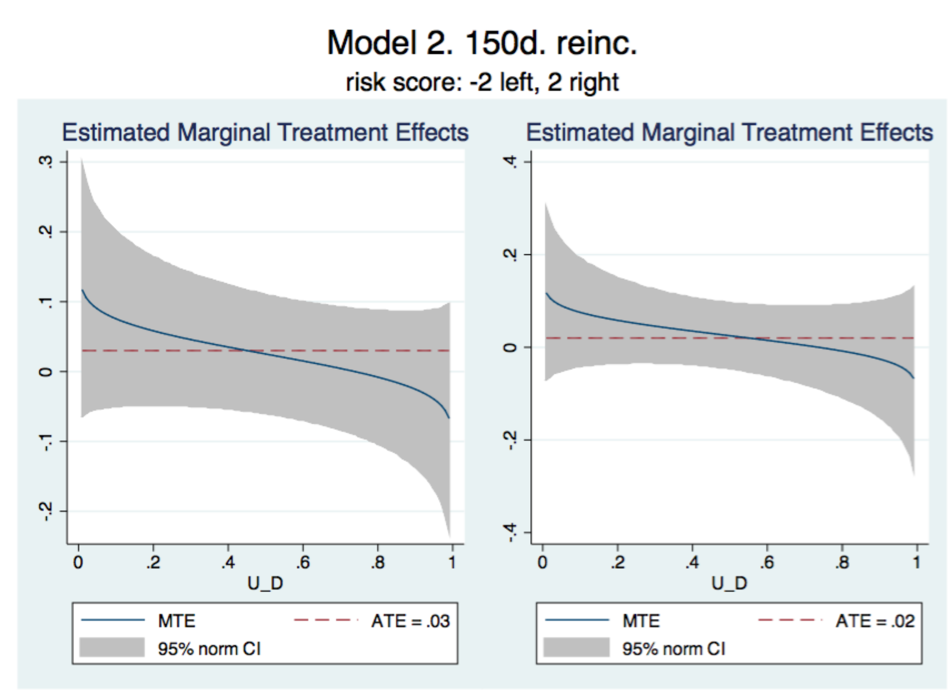


Figure 93. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 150-day threshold, outcome model #2, relative RST = -1 and relative RST = +1.

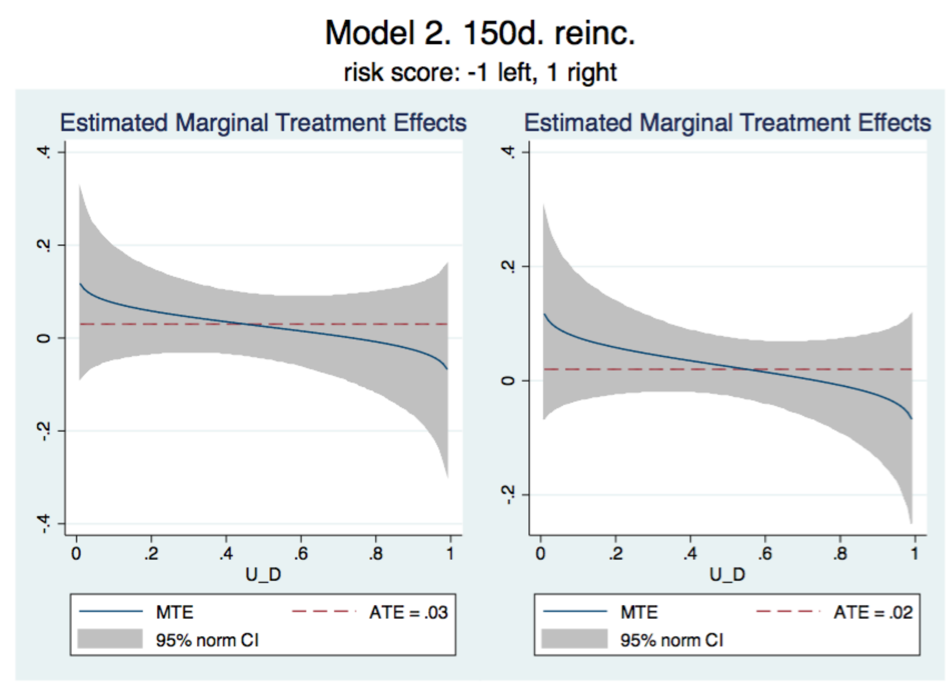


Figure 94. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 180-day threshold, outcome model #2, relative RST = -4 and relative RST = +4.

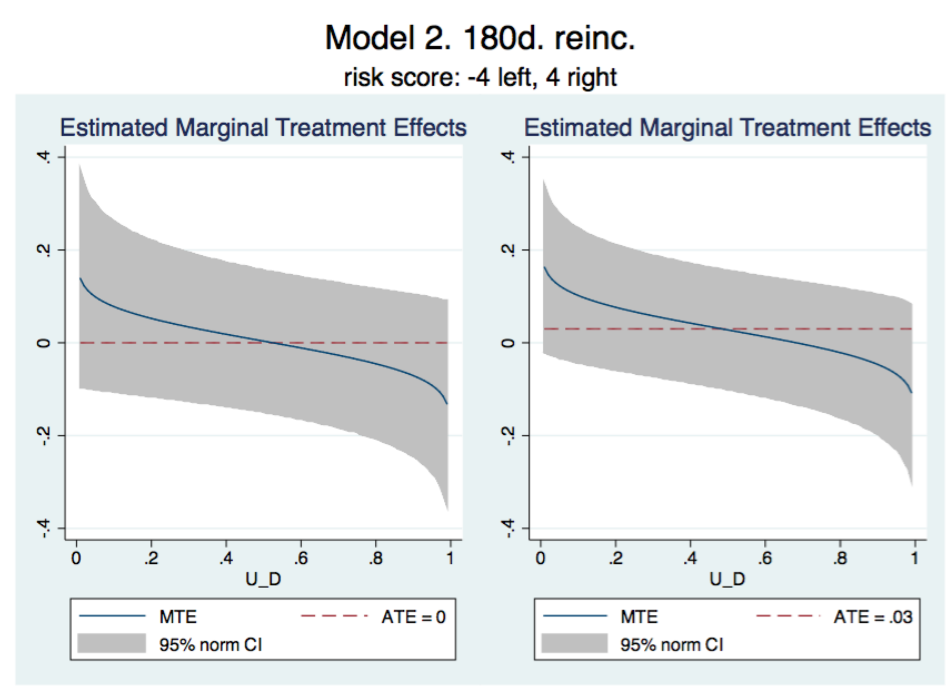
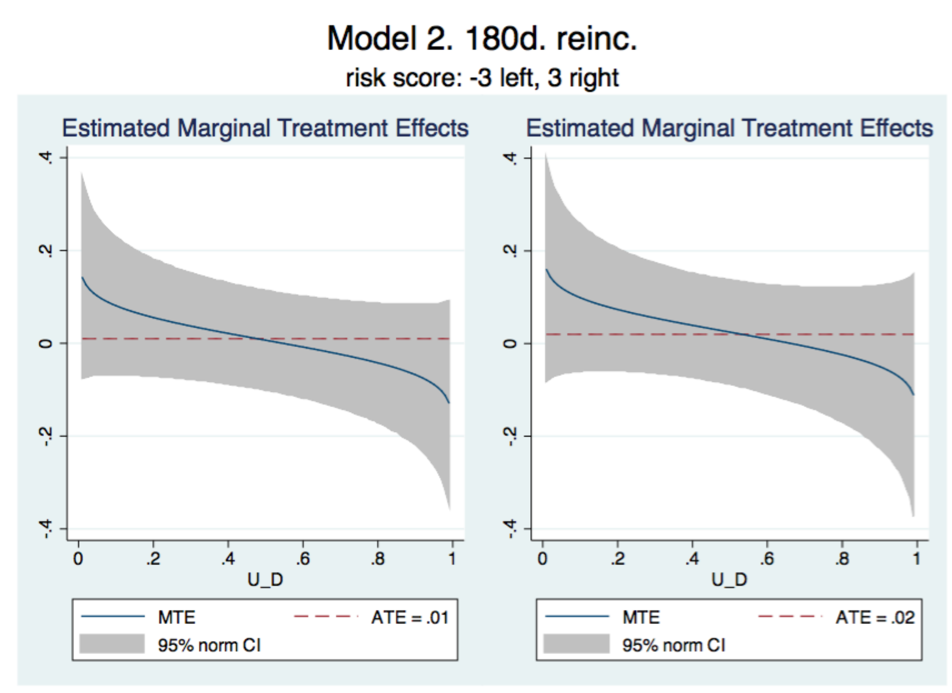


Figure 95. Average and marginal prison peer effects of relative risk score on releasees' recidivism at the 180-day threshold, outcome model #2, relative RST = -3 and relative RST = +3.



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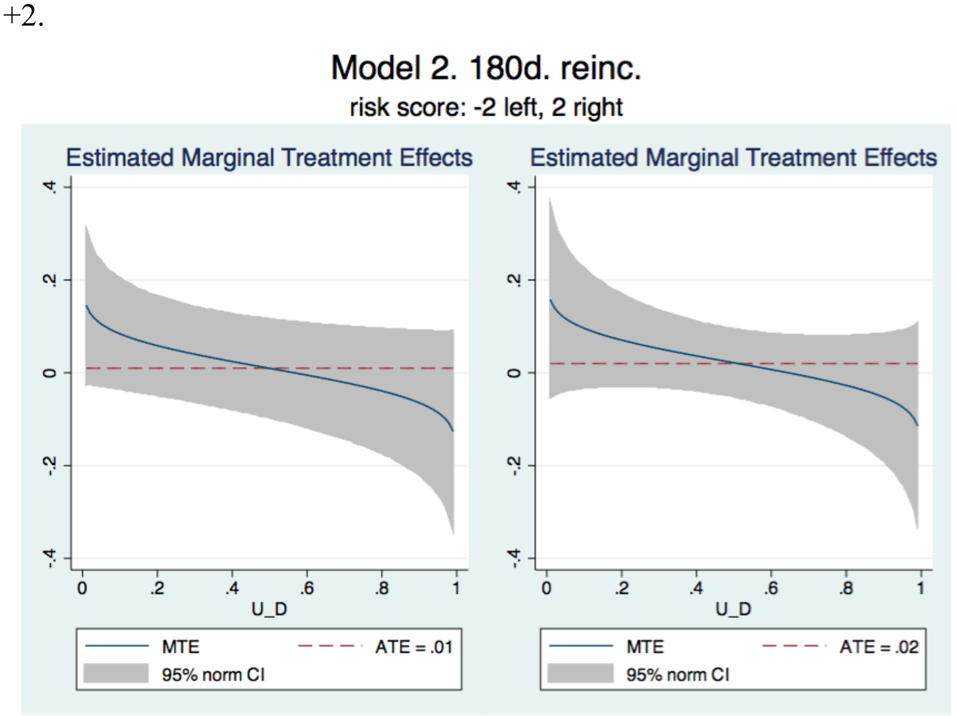

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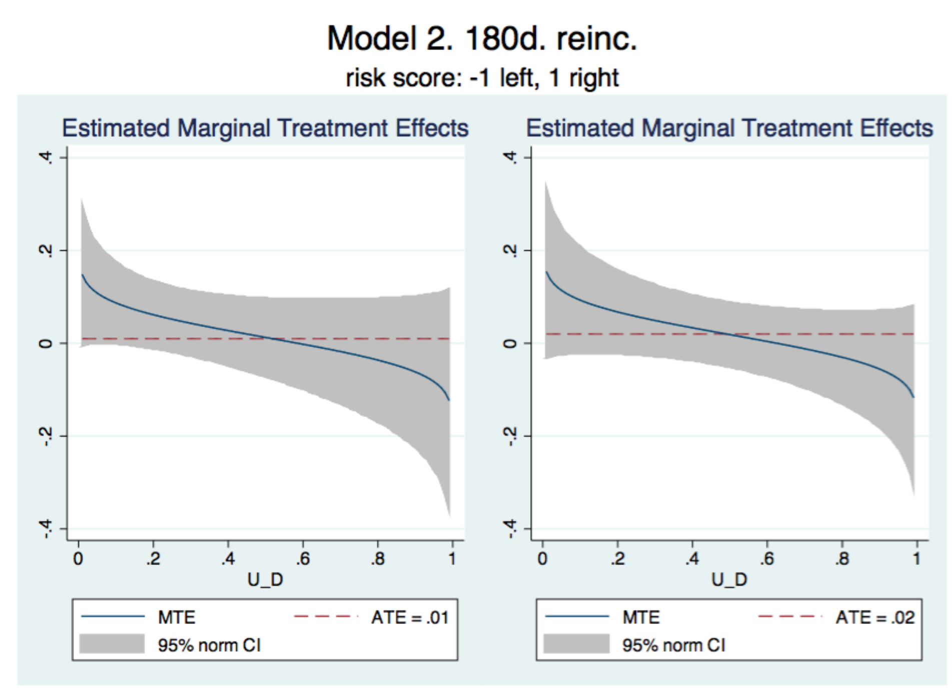

Chapter 2 Appendix

LSIR Scoring Sheet for the Pennsylvania Deparment of Corrections.

LSI•R: The Level of Service Inventory • Revised

by D. A. Andrews, Ph.D., and James L. Bonta, Ph.D.

Remember, the rating scale is as follows:

- **3: A satisfactory situation with no need for improvement**
- **2: A relatively satisfactory situation with some room for improvement evident**
- **1: A relatively unsatisfactory situation with a need for improvement**
- **0: A very unsatisfactory situation with a very clear and strong need for improvement**

Family/Marital

		Question Numbers
Dissatisfaction with marital or equivalent situation	3 2 1 0	23.
Non-rewarding, parental	3 2 1 0	24.
Non-rewarding, other relatives	3 2 1 0	25.
Criminal-Family/Spouse	No Yes	26.

Accommodation

Unsatisfactory	3 2 1 0	27.
3 or more address changes last year	No Yes	28.
High crime neighborhood	No Yes	29.

Leisure/Recreation

Absence of recent participation in an organized activity	No Yes	30.
Could make better use of time	3 2 1 0	31.

Companions

A social isolate	No Yes	32.
Some criminal acquaintances	No Yes	33.
Some criminal friends	No Yes	34.
Few anti-criminal acquaintances	No Yes	35.
Few anti-criminal friends	No Yes	36.

Alcohol/Drug Problem

Alcohol problem, ever	No Yes	37.
Drug problem, ever	No Yes	38.
Alcohol problem, currently	3 2 1 0	39.
Drug problem, currently Specify type of drug:______	3 2 1 0	40.
Law violations	No Yes	41.
Marital/Family	No Yes	42.
School/Work	No Yes	43.
Medical	No Yes	44.
Other indicators Specify:______	No Yes	45.

Emotional/Personal

Moderate interference	No Yes	46.
Severe interference, active psychosis	No Yes	47.
Mental health treatment, past	No Yes	48.
Mental health treatment, present	No Yes	49.
Psychological assessment indicated Area:______	No Yes	50.

Attitudes/Orientation

Supportive of crime	3 2 1 0	51.
Unfavorable toward convention	3 2 1 0	52.
Poor, toward sentence	No Yes	53.
Poor, toward supervision	No Yes	54.

LSI•R: The Level of Service Inventory • Revised

by D. A. Andrews, Ph.D., and James L. Bonta, Ph.D.

Remember, the rating scale is as follows:

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Drug problem, ever	No Yes	38.
Alcohol problem, currently	3 2 1 0	39.
Drug problem, currently Specify type of drug:__________	3 2 1 0	40.
Law violations	No Yes	41.
Marital/Family	No Yes	42.
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Other indicators Specify:__________	No Yes	45.

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Attitudes/Orientation

Supportive of crime	3 2 1 0	51.
Unfavorable toward convention	3 2 1 0	52.
Poor, toward sentence	No Yes	53.
Poor, toward supervision	No Yes	54.

RST Scoring Sheet for the Pennsylvania Department of Corrections.

A

Inmate Name:	
Inmate Number:	
Administration Date:	
Staff Member:	

Correctional Planning is Required?

YES ☐ **NO** ☐

Circle appropriate response for each item below:

B

1) Offender's age at first arrest?		
	age 16 or older	0
	age 15 or younger	1
2) Current age of offender?		
	44 & older	0
	25 - 43	1
	24 & younger	2
3) Prior convictions as an adult?		
	0	0
	1	1
	2 or more	2
4) Sanctioned for behavior in institutional setting?		
	no	0
	yes	1
5) Violation of a period of community supervision?		
	no	0
	yes	1

C **Override Considerations**

(if one or more of the following are checked "Yes" override to full assessment battery)

1) History of Domestic Violence?

YES ☐ **NO** ☐

2) Two or more DUIs?

YES ☐ **NO** ☐

3) Current sex offense?

YES ☐ **NO** ☐

4) Violence indicated?

6) Failed to attain 12th grade education?		
	no	0
	yes	1
7) Alcohol or Other Drug problem during lifetime?		
	no	0
	yes	1

YES ☐ **NO** ☐

Final Score ☐

Please Circle Risk Level

Low (0 - 4)	**Medium (5 - 6)**	**High (7 - 9)**

Chapter 5 Appendix

Supporting documents from SCI-Dallas.

CELL CHANGE REQUEST FORM

DATE MOVE MADE:______________

1. INMATE REQUESTING TO MOVE

D.O.C. #	NAME	RACE	BLK	SEC	LEVEL	CELL	BUNK #	CURRENT CELLMATE (IF ANY) D.O.C. #	CURRENT CELLMATE (IF ANY) NAME

REASON YOU WANT TO MOVE INTO BELOW LISTED INMATE'S (SECTION 2) CELL

REQUESTING INMATE'S SIGNATURE	DATE

2. INMATE AGREEING TO THE MOVE

D.O.C. #	NAME	RACE	BLK	SEC	LEVEL	CELL	BUNK #	CURRENT CELLMATE (IF ANY) D.O.C. #	CURRENT CELLMATE (IF ANY) NAME

REASON YOU WANT TO MOVE INTO BELOW LISTED INMATE'S (SECTION 2) CELL

AGREEING INMATE'S SIGNATURE	DATE

3. OFFICER RECOMMENDATION

AM OFFICER	REMARKS
YES ☐ NO ☐	
PM OFFICER	REMARKS
YES ☐ NO ☐	

IF HOUSING OFFICER IS INITIATING REQUEST, STATE REASON FOR REQUESTING CELL CHANGES:

OFFICERS SIGNATURE:	DATE:

4. UNIT MANAGER

UNIT MANAGER	REMARKS
APPROVED ☐ DISAPPROVED ☐	
UNIT MANAGER/AREA LIEUTENANT SIGNATURE:	DATE:

5. EMPLOYMENT/VOCATIONAL COORDINATOR

EMPLOYMENT/VOCATIONAL COORDINATOR SIGNATURE	DATE

IF THIS CELL MOVE IS APPROVED, ANOTHER CELL MOVE WILL NOT BE GRANTED FOR A MINIMUM OF 6 MONTHS

cc: DC-15 DC-14

Vacant Cell Report

Date: 25 March 2013

H/U	CODE* CELL#/BUNK	RACE	CODE* CELL#/BUNK	RACE	CODE* CELL#/BUNK	RACE	CODE* CELL#/BUNK	RACE	CODE* CELL#/BUNK	RACE
AA	8-1	B								
AB	33 CM		36 CM		39 CM		76 INF			
	34 CM		37 CM		47-1	H				
	35 CM		38 CM		13-2 Z					
BA	6-1 Z	B	34-1	H	67-1	W	100-1 INF			
	8-2 ATA	W	44 CM		68-1 ID	B				
	28-1	B	65-1 INF	W	80-2	B				
CA	1-2	B	36-1 ATA	W	95-1	B				
	5-1	W	46-1ATA	W						
	11-1	B	92-2	B						
DA										
DB	4-2 Z	B	39-2	W	74-1	W				
	31-1	W	57-1	W						
	35-1	B	69-1 ATA	B						
EA	26-1	B								
	88-1	H								
	94-1	B								
FA	40-2	H								
	43-2Z	B								
	78-2	W								
GA	4-2	H	27-2	B						
	12-2	W	67-2	B						
	22-2	B								

***CODES:** **ATA** **I.D.** – Property needs removed **CM** – Closed/Maintenance **Empty** – Open Cell

Inf. – Infirmary Admit **Hold** – Unit Manger Hold **S**-Single Cell

Vacant Cell Report

Date: 25 March 2013

H/U	CODE* CELL#/BUNK	RACE	CODE* CELL#/BUNK	RACE	CODE* CELL#/BUNK	RACE	CODE* CELL#/BUNK	RACE	CODE* CELL#/BUNK	RACE
HA	1		41 INF		65 INF					
	22		57							
	40 INF		60 HOLD							
IA	6-2	W	83-2	W						
	9-1	W	27 INF							
	33-2	H								
JA	4-1 ATA	B	33-2 ATA	B	79-2 ATA	W	96-1	W		
	5-2	W	42-2	W	83-1	W	98-1 ATA	W		
	10-1	B	47-2	W	85-2	W				
LA	16-1 ATA	B	23-1	W						
	46-2	W	42-2	B						
	15-2 HOLD	B								
MB	14-2	B								
MC	2-2	B	11-1 ATA	W	16-2	B	20-2 / 21-2	B/W		
	3-2	W	14-2	W	17-2	B	19-2	W	7 Z	
	4 EMPTY		15-2	B	18-2	W	22-2	W	23 Z	
O-A										
O-B										
OC	1002-14 ATA									
	1001-18									

***CODES:** ATA **I.D.** - Property needs removed **CM** – Closed/Maintenance **Empty** – Open Cell

Inf. – Infirmary Admit **Hold** – Unit Manger Hold **S**- Single Cell

INMATE MUST TURN IN PASS IMMEDIATELY UPON COMPLETION OF THE PURPOSE FOR PASS

INMATE PASS SLIP Date ____________

No. ____________ Name ____________

Housing Unit ____________ Cell Assignment ____________

Destination ____________

ISSUING AUTHORITY	SIGNATURE	TIME OUT TIME IN
DESTINATION AUTHORITY	SIGNATURE	TIME IN TIME OUT
RETURN AUTHORITY	SIGNATURE	TIME OUT

```
USER ID: U435983          PA DEPT. OF CORRECTIONS      PRODUCTION    GI301BM
TERM ID: 6A0E           INMATE BED ASSIGNMENT SYSTEM        DATE:  3/26/2013
SESSION: 1     FACILITY STATISTICS FOR Dallas               TIME:  9:43
==============================================================================
                Cells/Dorms  Beds       |            Cells/        Available
          Total:    1214      2214      |  Security  Dorms   Beds     Beds
N/A Maintenance:       8        16      |   Level 1:     0      0        0
N/A Non-Custody:       0         0      |   Level 2:    56    220       10
                                        |   Level 3:  1029   1813       53
          Cells:    1208      2094      |   Level 4:    23     46       13
    Dormitories:       6       120      |   Level 5:   106    135       20
                                        |     Other:     0      0        0
                                        |
       Handicap Beds:      32           |--------------------------------------
     1/2 Double Beds:      86           |           Ethnic Counts  Percents
       Cells Doubled:     787           |                Asian:    2    0.10 %
                                        |  American Indian:    0    0.00 %
------------- Inmate Counts ----------  |                Black: 1149   55.29 %
  Physically Present:    2078           |             Hispanic:  238   11.45 %
       Writ/Furlough:      10           |                White:  678   32.63 %
          Unassigned:       3           |                Other:    8    0.38 %
==============================================================================
F1 LOGOFF, F6 HELP, F18 (SHIFT/F6) FUNCTION KEY LIST
```

```
PA DEPT. OF CORRECTIONS         INMATE BED ASSIGNMENT SYSTEM     RUN:   GR121RPT
COMPUTER SERVICES                      AVAILABLE BEDS            DATE:  3/26/2013
REMOTE PRINT TIME  9:41                  Dallas                  PAGE:          1
=================================================================================
BUILDING: A   SECTION: A
---------------------------------------------------------------------------------
     CELL      BED       HOUSING     HANDICAP      SECURITY          BED
     DORM     NUMBER     STATUS      ACCESSIBLE     LEVEL           STATUS
     ----     ------     -------     ----------    --------      ------------
     1008       2          TCS          NO            3           AVAILABLE
     1010       1          TCS          NO            3           AVAILABLE

    2 AVAILABLE BEDS FOR BUILDING A  SECTION A
```

TCU

PA DEPT. OF CORRECTIONS INMATE BED ASSIGNMENT SYSTEM RUN: GR121RPT
COMPUTER SERVICES AVAILABLE BEDS DATE: 3/26/2013
REMOTE PRINT TIME 9:41 Dallas PAGE: 2

BUILDING: A SECTION: B

CELL DORM	BED NUMBER	HOUSING STATUS	HANDICAP ACCESSIBLE	SECURITY LEVEL	BED STATUS
1013	2	GP	NO	3	Z-CODE
2047	2	GP	NO	3	AVAILABLE
2076	1	GP	NO	3	INFIRMARY

3 AVAILABLE BEDS FOR BUILDING A SECTION B

single cell (but in double)

PA DEPT. OF CORRECTIONS INMATE BED ASSIGNMENT SYSTEM RUN: GR121RPT
COMPUTER SERVICES AVAILABLE BEDS DATE: 3/26/2013
REMOTE PRINT TIME 9:41 Dallas PAGE: 3

BUILDING: B SECTION: A

CELL DORM	BED NUMBER	HOUSING STATUS	HANDICAP ACCESSIBLE	SECURITY LEVEL	BED STATUS
1006	2	GP	NO	3	RHU
1007	1	GP	NO	3	TEMPTRANSFER
1008	1	GP	NO	3	WRIT
1028	2	GP	NO	3	AVAILABLE
1034	2	GP	NO	3	AVAILABLE
1044	1	GP	NO	3	AVAILABLE
1044	2	GP	NO	3	AVAILABLE
2067	2	GP	NO	3	AVAILABLE
2068	1	GP	NO	3	RHU
2080	1	GP	NO	3	AVAILABLE
2094	1	GP	NO	3	AVAILABLE
2100	2	GP	NO	3	MEDICAL

12 AVAILABLE BEDS FOR BUILDING B SECTION A

PA DEPT. OF CORRECTIONS | INMATE BED ASSIGNMENT SYSTEM | RUN: GR121RPT
COMPUTER SERVICES | AVAILABLE BEDS | DATE: 3/26/2013
REMOTE PRINT TIME 9:41 | Dallas | PAGE: 4

BUILDING: C SECTION: A

CELL DORM	BED NUMBER	HOUSING STATUS	HANDICAP ACCESSIBLE	SECURITY LEVEL	BED STATUS
1001	2	GP	NO	3	AVAILABLE
1003	2	GP	NO	3	TEMPTRANSFER
1005	2	GP	NO	3	AVAILABLE
1011	2	GP	NO	3	AVAILABLE
1036	2	GP	NO	3	WRIT
1046	2	GP	NO	3	WRIT
2092	1	GP	NO	3	AVAILABLE
2095	2	GP	NO	3	AVAILABLE

8 AVAILABLE BEDS FOR BUILDING C SECTION A

PA DEPT. OF CORRECTIONS | INMATE BED ASSIGNMENT SYSTEM | RUN: GR121RPT
COMPUTER SERVICES | AVAILABLE BEDS | DATE: 3/26/2013
REMOTE PRINT TIME 9:41 | Dallas | PAGE: 5

BUILDING: D SECTION: B

CELL DORM	BED NUMBER	HOUSING STATUS	HANDICAP ACCESSIBLE	SECURITY LEVEL	BED STATUS
1004	2	GP	NO	3	Z-CODE
1031	2	GP	NO	3	AVAILABLE
1035	2	GP	NO	3	TEMPTRANSFER
1039	2	GP	NO	3	AVAILABLE
2057	2	GP	NO	3	INFIRMARY
2069	2	GP	NO	3	TEMPTRANSFER
2074	2	GP	NO	3	AVAILABLE

7 AVAILABLE BEDS FOR BUILDING D SECTION B

Supporting documents from SCI-Pittsburgh.

pennsylvania
DEPARTMENT OF CORRECTIONS

INCOMING INMATE DOUBLE CELLING CHECKLIST

This form must be completed and signed by a Unit Manager or Commissioned Officer prior to double celling an incoming inmate into the IHU or RHU.

Inmate name and number

Inmate name and number

Are the inmates similar in age?	YES	NO
Are the inmates from the same county jail?	YES	NO
Are the inmates the same race?	YES	NO
Are the inmates similar in physical size/stature?	YES	NO
Does either inmate have a mental health history?	YES	NO
Does either inmate have any concerns with double celling?	YES	NO
Do the inmates have similar institutional/criminal histories?	YES	NO
Does either of the inmates have a preference affecting double-celling compatibility? If YES; note below: (staff is to ask the inmate if he has preferences affecting double-celling compatibility, but shall not offer the inmate choices.)	YES	NO

___

Is there any additional information received from the transferring authority? ______________	YES	NO

Is there any other information available which would be a concern with double celling these inmates? ______________

___

The above questions are to be answered after reviewing any information received upon reception and from interviewing the inmates. A suicide indicator checklist is also to be completed and reviewed.

Approved for double celling ______________________ Date________
(Unit Manager or Commissioned Officer)

cc: DC-15, DC-14 files

SCI Pittsburgh | 3001 Beaver Avenue | Pittsburgh, PA 15233 | 412.761.1955 | www.governor.state.pa.us

DATE OF REQUEST [redacted]

ʒy making this request, we each agree to, and understand, the following:

1. This is only a request to have a certain cell partner. The Unit Manager Team will make the final determination if this request will be honored. The Unit Management Team includes the Unit Manager, Counselor, Sergeant and Range Officer.

2. This request is for a cell partner *only.* The Unit Management Team will determine what cell we will move to. Request for specific cells will not be honored.

3. Once this request is submitted, it can not be revoked. If we submit more than one request, they will all be void.

4. The Unit Management Team will determine when the move will be made.

5. Request involving inmates from two different housing units must be approved by both Unit Managers involved.

6. Once the move is made, we may not request another move for 90 days.

7. The Unit Management Team many move one or both of us at any time to meet operational needs.

8. If one of us is moved out of the cell for any reason (RHU, TC, Medical, Etc.), this request is void, and will not be considered when the inmate returns to the housing unit. A new request will have to be submitted.

ign below to indicate your understanding of, and agreement with, the above items:

[redacted]	[redacted]	[redacted]
'RINT NAME AND NUMBER	CURRENT CELL	SIGNATURE
[redacted]	[redacted]	[redacted]
'RINT NAME AND NUMBER	CURRENT CELL	SIGNATURE

– 2 Unit Sergeant's Signature Comments: [redacted]

- 10 Unit Sergeant's Signature Comments: [redacted]

FOR UNIT MANAGEMENT TEAM USE ONLY / DO NOT WRITE BELOW THIS LINE

From: Cahill, Leo
Sent: Thursday, October 27, 2011 5:45 AM
To: CR-PIT Bed Mgmt
Subject: SCIP Daily Housing Unit Changes (w cable)

SCI PITTSBURGH
BED MANAGEMENT SYSTEM
DAILY HOUSING UNIT / CELL CHANGES

HOUSING UNIT: A100	SUBMITTING STAFF NAME CO1 Cahill	DATE: 10/27/11

INMATE INFORMATION			OLD ASSIGNMENT				NEW ASSIGNMENT				TIME		CABLE
DC#	Name		Unit	Cell	Bed		Unit	Cell	Bed		24 Hr		Yes/No
[redacted]													

pennsylvania
DEPARTMENT OF CORRECTIONS

SCI Pittsburgh

SUBJECT: Unit F Operation Schedule

TO: All Concerned

DATE: October 4, 2012

FROM: Michael Zaken
DSFM

0610: Count Time
0641-0645: Blues to Breakfast/Insulin/Blood Work
0645-0700: Send GP to Eat
0700-0800: Blues Take Shower (Monday through Friday)
0700-0800: <u>Blues River Side not cleaning their cell</u> – Shower/Cell Cleaning (Sundays)
0800: Blues Finish Showers
0830: Send GP to Yard
0900: Blues to Chapel (Wednesdays)
0900-1000: Blues in Day Room
1030-1100: Blues to Lunch
1100: Send Blues to Yard
1100: GP to Lunch
1200: Blues Lock In
1210: Count Time
1255: Pass Movement
1330: Blues to Chapel (Monday)
1330: Blues to Library (Tuesdays & Thursdays)
1330-1545: GP Yard and Shower Time
1415-1545: Blues to Chapel for Jumah (Fridays)
1545: Everyone Lock In
1550: Count Time

1700: Blues to Dinner
1730: GP to Dinner
1800: F Unit Pill Line
1815: Blues Lock In
1830: Library (Tuesdays & Fridays)
1830: GP to Yard
1900-2000: Blues in Day Room
2000: GP Out for Phone & Showers
2045: Everyone Lock In
2100: Count Time

0600-1600: Commissary (Tuesdays Only)
0600-1400: Pick Up Supplies (Tuesdays Only)
0600-1400: Caustics Pick-Up (Mondays & Fridays Only)
0945-1030: Linen Exchange (Wednesdays Only)

- CO distributes and monitors Cleaning Supplies
- All supplies returned to supply room at 0830 and 1520
- No Blues are worn to showers (Boxers, Tee-shirt & Towel wrapped around mid-section)
- Cells are to be secured during and after shower, and at all times when Line Movement is finished

Approved: ______________________________

Mark V. Capozza, Superintendent

Bed assignment survey and its results.

Thank you for taking the time to answer a few questions regarding the process by which inmates are placed in beds.

We are interested in better understanding how decisions to place inmates into cells are made. We are particularly interested in any factors, such as (but not limited to) custody level (PACT), risk level (RST/LSIR), inmate demographics (age, race, etc.), inmate personal preferences, separation issues, commitment crime types, and bed availability, that might affect inmate bed placements. We are interested in how important each of those factors is in the decision making process. We are also interested in the bed placement decision making process itself.

Please answer each of the questions as completely as possible. More information is better than less. Additionally, if you can, please attach copies of any official checklists, guidelines, or procedures that are used to place inmates.

Q1. Please describe how inmates are assigned to beds at different levels of your institution (e.g., building, section, cell). Please provide as much information as you think necessary to fully describe the placement process, keeping in mind that we are especially interested in the factors that determine inmate placements and how those factors are weighted (i.e., how important each of the factors is). For this question, we are interested in the process that applies to the general population, that is, most of your inmates. For example, the procedure may attempt to double-cell inmates if their commitment crime types are similar, their custody levels are the same, and there is no separation issue between them. Or, the procedure may assign inmates of the same custody level to one building, but within the building, inmates are assigned to cells based on bed space availability.

If you have official guidelines, checklists, or procedures that dictate how inmates are assigned to cells in your facility, please attach the documentation that describes the procedures.

Q2. Is the process used to place inmates the same throughout your facility or does it differ by building or section within your facility? If some buildings or sections in your facility place inmates using a different process, could you please describe the different processes, indicating to which building or section they apply? (Here, we are interested in any special cases that might exist.)

Q3. Why are inmates generally moved from cell to cell during their stays in your institution? Could you please list some reasons for inmate moves (e.g., changes in custody level) and indicate how common they are?

Q4. Who is responsible for overseeing the inmate placement process? If we may contact him/her with further questions, please provide his/her contact information.

Results: Factors in PADOC initial placements

Shaded “1” indicates the factor is considered

	Facilities																									
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
Inmate characteristics																										
Race	1	.	1	.	1	.	1	1	1	1	1	1	1	1	.	1	1	.	1	1	.	.	.	1	.	.
Age	.	.	1	.	1	1	1	1	1	.	1	1	.	1	1	1	1	.	1	1	.	.	.	1	.	1
Stature/Size	.	.	1	.	1	1	.	1	.	.	.	.	1	.	1	.	1	1	.	.	.	.	.	.	.	.
Sexual orientation	.	.	.	.	1	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.
Religion	1	.	.	.	.	.	.	.	1	.	.	.	1	1	.	.	.	.	1	.	.	.	.	.	.	.
Temperament/Personality	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	1	1	.	.	.	.	.	.	1
Hygiene	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Smoking preference	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.
Family members	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	1	.
Geographic origin	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.
Commit status	.	.	1	.	1	.	1	1	.	.	.	.	.	.	1	.	.	.	1	1	.	.	.	.	1	1
Criminal/incarceration																										
Current offense	.	.	1	.	1	.	.	.	.	.	1	.	.	.	.	1	1	1	.	1	.	1	.	.	.	.
Sentence/Time to min	1	1	1	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	1	1	.	.	.	.	.	.
Criminal/incarceration history	.	.	.	.	.	1	.	.	1	.	1	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.
Number of previous cellmates	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.
Code characteristics																										
Medical	1	1	1	.	1	1	1	.	1	.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	.	1
Mental	.	1	1	.	.	.	1	.	1	1	1	.	1	1	1	.	.	1	1	1	.	1	1	1	1	.
Program	1	1	1	1	1	1	1	1	.	1	.	1	1	1	1	1	1	1	.	1	1	1	1	1	1	1
Work	.	.	1	.	.	1	.	1	1	1	.	.	.	.	1	1	.	1	1	.	.	.	1	.	1	.
Housing	.	.	.	.	1	1	1	.	.	.	.	.	1	1	1	.	.	1	1	.	.	1	.	1	.	.
Risk	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Security	.	.	.	.	.	.	.	.	.	.	1	.	1	1	.	1	.	1	.	.	.	.	.	.	.	.
Gang	1	.	1	.	1	1	1	.	1	.	1	.	1	1	.	.	.	.	1	.	.	.	.	1	.	.
Victim/Predator	1	.	.	.	.	1	1	.	1	.	.	1	1	1	1	.	.	1	1	.	.	.	.	1	.	.
Escape	.	.	.	.	1	.	1	1	1	.	1	.	1	.	.	.	.	1	.	.	.	.	.	.	.	.
Behavior	.	1	1	.	1	1	1	.	1	.	.	.	.	1	.	.	.	.	1	1	.	.	.	1	1	.
Custody level	1	1	1	.	.	1	1	1	1	.	1	1	1	.	1	1	1	.	1	1	.	1	1	1	.	.
O code	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Separations/Preferences																										
Administrative separation	.	.	.	.	1	.	1	.	.	.	.	.	1	1	1	.	.	.	.	1	.	1	.	.	1	1
Informal separation	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.
Inmate agreement	.	.	.	1	.	1	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Inmate request/preference	1	.	.	.	.	.	1	.	1	.	1	.	.	1	1	.	.	.	.	.	.	.	1	.	.	.
Facility characteristics																										
Design	.	.	.	.	.	1	1	1	.	.	.	.	1	.	1	1	1	.	.	.	.	.	.	.	1	.
Bed space	.	.	1	.	1	.	1	1	.	1	1	1	.	1	1	1	.	1	1	1	.	1	1	1	1	1
Block custody level ratio	.	.	.	.	1	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.
Counselor case load	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.
Unit manager override	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.

Results: Factors in PADOC within-facility moves

Shaded "1" indicates the factor is considered

	Facilities																									
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
Inmate requests																										
Inmate agreement	.	.	.	1	.	1	1	.	1	.	.	.	.	1	1	1	.	.	1	1	.	.	1	1	.	.
Inmate preference	1	1	1	.	.	.	1	.	.	1	1	1	.	.	.	.	.	.	1	.	.	1	.	.	1	1
Formal separations	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Local separation	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	1	.	.
Security & Behavior																										
Security	1	1	.	.	.	.	1	1	1	1	.	.	1	.	1	1	.	.	.	.	.	1	1	.	1	.
Escape	.	.	.	.	1	.	.	.	.	1	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.
Incompatibility	.	.	1	1	.	.	1	1	.	.	.	.	.	1	.	.	1	.	1	1	.	1	.	.	1	1
Relationship issues	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.
Negative adjustment	.	.	1	.	1	.	1	.	.	1	1	.	1	.	1	1	.	.	1	.	1	.	.	.	.	.
Positive adjustment	.	.	.	.	.	.	1	.	1	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	1
Staff/inmate conflict	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Status changes																										
Medical	.	.	1	1	1	1	.	.	.	1	1	1	1	.	1	1	1	1	1	1	1	.	1	1	.	.
Mental health	.	.	.	.	.	.	.	.	.	.	1	.	.	.	1	1	.	.	.	.	.	.	1	.	.	.
Program	1	1	1	.	1	1	.	1	.	1	1	.	1	.	1	.	1	1	.	1	.	.	1	1	.	.
Work	.	.	1	.	.	1	.	1	.	.	1	.	.	.	1	1	.	.	.	.	.	1	.	.	1	.
Custody level	.	.	1	.	.	1	.	.	.	1	.	1	1	.	.	1	1	.	.	.	.	.	.	.	.	.
Housing	.	.	.	1	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Institutional issues																										
Institutional needs	.	.	1	.	.	.	1	.	.	.	.	1	.	.	.	1	.	.	.	.	1	.	.	.	1	.
Bed space	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	1	.	.	.	.
Sentence length	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.

Chapter 8 Appendix

Choice linear probability model regression output.

Source	SS	df	MS
Model	93157099.3	90	1035078.88
Residual	119144929	10040	11867.0248
Total	212302028	10130	20957.7521

Number of obs	= 10131
F(90, 10040)	= 87.22
Prob > F	= 0.0000
R-squared	= 0.4388
Adj R-squared	= 0.4338
Root MSE	= 108.94

total_tt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cellsqft_tt_fa	-.2296038	.1073454	-2.14	0.032	-.4400223	-.0191854
tier_tt_fa	4.606217	2.241488	2.05	0.040	.212452	8.999981
c_time2r_tt	.1885017	.0278109	6.78	0.000	.1339868	.2430166
r_age	-.068642	.1501978	-0.46	0.648	-.3630597	.2257757
r_black	1.969174	3.228649	0.61	0.542	-4.359626	8.297973
r_married	-4.814642	4.148375	-1.16	0.246	-12.94629	3.317004
r_islam	-2.789621	3.669108	-0.76	0.447	-9.981808	4.402566
r_urban	.9832676	2.978727	0.33	0.741	-4.855634	6.822169
r_maxsent	.1888018	.0398963	4.73	0.000	.1105971	.2670065
r_cust_gt3	-1.261988	3.004857	-0.42	0.675	-7.152109	4.628133
r_misAB	-4.528932	3.195086	-1.42	0.156	-10.79194	1.734076
r_hadtc	-5.697554	5.971884	-0.95	0.340	-17.40364	6.008535
r_ever_ac_sol	-23.97363	4.0909	-5.86	0.000	-31.99261	-15.95465
r_3charge	.4412901	2.332159	0.19	0.850	-4.130209	5.012789
r_p_medlim	-5.322322	3.384867	-1.57	0.116	-11.95734	1.312695
r_p_hsgrad	2.098427	2.428911	0.86	0.388	-2.662725	6.85958
r_p_had_job	-2.197671	2.620452	-0.84	0.402	-7.334282	2.93894
r_p_prob_drugalc	-22.19149	6.182035	-3.59	0.000	-34.30952	-10.07346
r_p_prob_mh	-10.91355	2.543387	-4.29	0.000	-15.8991	-5.928001
r_p_usvet	1.459334	7.860959	0.19	0.853	-13.94972	16.86839
r_p_iq	.1915739	.0865646	2.21	0.027	.0218899	.3612578
r_18under_1arr	-1.591754	2.799412	-0.57	0.570	-7.079162	3.895654
c_age	.4690279	.157199	2.98	0.003	.1608863	.7771694
c_black	4.43525	3.229106	1.37	0.170	-1.894445	10.76495
c_married	5.751475	4.139993	1.39	0.165	-2.363741	13.86669
c_islam	-2.560275	3.606853	-0.71	0.478	-9.63043	4.50988
c_urban	-1.077964	3.001302	-0.36	0.719	-6.961117	4.80519
c_maxsent	.0411899	.0080563	5.11	0.000	.0253979	.056982
c_cust_gt3	-5.274924	2.922427	-1.80	0.071	-11.00347	.4536187
c_misAB	-3.987415	2.962136	-1.35	0.178	-9.793796	1.818965
c_hadtc	-3.250013	5.708691	-0.57	0.569	-14.44019	7.940164
c_ever_ac_sol	-7.366068	3.979795	-1.85	0.064	-15.16726	.435127
c_3charge	6.049312	2.350284	2.57	0.010	1.442285	10.65634
c_p_medlim	-3.128476	3.363723	-0.93	0.352	-9.722047	3.465095
c_p_hsgrad	4.988381	2.434307	2.05	0.040	.2166523	9.760109
c_p_had_job	-7.791509	2.689564	-2.90	0.004	-13.06359	-2.519426
c_p_prob_drugalc	-21.70291	6.177288	-3.51	0.000	-33.81163	-9.594188
c_p_prob_mh	-7.92913	2.512115	-3.16	0.002	-12.85338	-3.004881
c_p_usvet	-12.02145	7.791695	-1.54	0.123	-27.29473	3.251838
c_p_iq	.1410386	.0818828	1.72	0.085	-.0194681	.3015453
c_18under_1arr	-4.004883	2.710787	-1.48	0.140	-9.318568	1.308803
c_apv	4.502809	4.012633	1.12	0.262	-3.362755	12.36837
c_hasPriorI	-2.595447	3.34256	-0.78	0.437	-9.147534	3.95664
r_pri_narr	-.683823	.2792653	-2.45	0.014	-1.231239	-.1364072
c_pri_narr	-1.2182	.2260091	-5.39	0.000	-1.661223	-.7751767
stretches	31.69085	1.098175	28.86	0.000	29.53821	33.8435
r_time2rel	.0026538	.0049259	0.54	0.590	-.0070019	.0123095
r_staytime	.1025271	.0047178	21.73	0.000	.0932793	.1117749
same_age	5.386562	2.481724	2.17	0.030	.5218852	10.25124
same_race	3.480549	2.759324	1.26	0.207	-1.928278	8.889377
same_married	8.378273	4.073426	2.06	0.040	.3935422	16.363
same_islam	8.22742	3.462665	2.38	0.018	1.439904	15.01494
same_urban	2.675539	2.877031	0.93	0.352	-2.964018	8.315096
same_cust_gt3	-1.231374	2.830429	-0.44	0.664	-6.779582	4.316833
same_misAB	-7.998774	2.627122	-3.04	0.002	-13.14846	-2.849089
same_hadtc	5.887665	5.523085	1.07	0.286	-4.938687	16.71402
same_ever_ac_sol	-4.969524	3.815687	-1.30	0.193	-12.44904	2.509987
same_3charge	4.675059	2.27772	2.05	0.040	.2102715	9.139847
same_p_medlim	.8338698	3.299603	0.25	0.800	-5.634012	7.301752
same_p_hsgrad	-.3283876	2.264969	-0.14	0.885	-4.768181	4.111406

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
same_p_had_job	.4882493	2.616932	0.19	0.852	-4.641461	5.617959
same_p_prob_drugalc	16.34843	6.120131	2.67	0.008	4.351747	28.34511
same_p_prob_mh	-.6295035	2.422175	-0.26	0.795	-5.377451	4.118444
same_p_usvet	-6.04654	7.66426	-0.79	0.430	-21.07002	8.976944
same_p_iq	4.186251	2.206604	1.90	0.058	-.1391345	8.511636
same_18under_1arr	-2.428243	2.419096	-1.00	0.316	-7.170155	2.31367
fac_tt						
CAM	-70.0726	6.161757	-11.37	0.000	-82.15088	-57.99432
CHS	20.44542	8.46314	2.42	0.016	3.855973	37.03487
COA	16.82359	7.181058	2.34	0.019	2.747281	30.8999
CRE	-34.79314	9.784659	-3.56	0.000	-53.97303	-15.61325
DAL	-5.48759	8.490231	-0.65	0.518	-22.13014	11.15496
FRA	-2.652818	9.562124	-0.28	0.781	-21.3965	16.09086
FRS	11.47568	6.666701	1.72	0.085	-1.592387	24.54375
FYT	14.55192	7.663412	1.90	0.058	-.4698992	29.57374
GRA	-47.10056	9.451037	-4.98	0.000	-65.62649	-28.57464
GRE	-4.697444	9.184936	-0.51	0.609	-22.70176	13.30687
GRN	8.134494	9.652968	0.84	0.399	-10.78726	27.05624
HOU	16.12592	6.842561	2.36	0.018	2.713128	29.53871
HUN	-55.3387	8.868636	-6.24	0.000	-72.723	-37.9544
LAU	-19.74355	10.14997	-1.95	0.052	-39.63953	.152416
MAH	65.24186	6.962907	9.37	0.000	51.59317	78.89056
MER	-8.320465	9.684256	-0.86	0.390	-27.30355	10.66262
PIT	-15.86536	22.40117	-0.71	0.479	-59.77614	28.04542
PNG	-36.70152	8.523598	-4.31	0.000	-53.40948	-19.99356
RET	58.77057	9.011181	6.52	0.000	41.10685	76.43429
ROC	-3.817339	7.841624	-0.49	0.626	-19.18849	11.55381
SMI	26.43316	8.577451	3.08	0.002	9.619635	43.24668
SMR	9.905253	7.094725	1.40	0.163	-4.001829	23.81234
WAM	-107.3855	15.66149	-6.86	0.000	-138.0851	-76.68582
WAY	-270.2839	79.04534	-3.42	0.001	-425.2286	-115.3392
_cons	40.8325	23.02107	1.77	0.076	-4.293411	85.95841

Outcome linear probability model regression output, rearrest.

Source	SS	df	MS
Model	515.448353	115	4.48215959
Residual	1942.16037	10015	.19392515
Total	2457.60873	10130	.242606982

Number of obs =	10131
F(115, 10015) =	23.11
Prob > F =	0.0000
R-squared =	0.2097
Adj R-squared =	0.2007
Root MSE =	.44037

has_postA	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
total_tt	-.0000623	.0000405	-1.54	0.124	-.0001416	.0000171
r_age	-.0064403	.0007348	-8.76	0.000	-.0078807	-.0049999
r_black	.0550587	.0163377	3.37	0.001	.0230335	.087084
r_married	-.0295916	.0168043	-1.76	0.078	-.0625314	.0033482
r_islam	.056033	.0152414	3.68	0.000	.0261569	.0859092
r_urban	.0201293	.0121873	1.65	0.099	-.0037602	.0440188
r_maxsent	-.0012654	.000162	-7.81	0.000	-.001583	-.0009478
r_cust_gt3	.023889	.0123911	1.93	0.054	-.0004	.048178
r_misAB	-.035922	.0151099	-2.38	0.017	-.0655405	-.0063036
r_hadtc	.0226796	.0279584	0.81	0.417	-.0321246	.0774837
r_ever_ac_sol	.0064064	.0166315	0.39	0.700	-.0261948	.0390075
r_3charge	.0219318	.0094451	2.32	0.020	.0034175	.0404462
r_p_medlim	-.0010638	.0136994	-0.08	0.938	-.0279174	.0257898
r_p_hsgrad	-.0912186	.0124244	-7.34	0.000	-.115573	-.0668642
r_p_had_job	.0654379	.0106321	6.15	0.000	.0445968	.086279
r_p_prob_drugalc	-.0234287	.0265954	-0.88	0.378	-.0755611	.0287037
r_p_prob_mh	.029336	.0104188	2.82	0.005	.0089131	.0497589
r_p_usvet	-.0371625	.0318306	-1.17	0.243	-.0995569	.0252319
r_p_iq	.0002044	.0003524	0.58	0.562	-.0004864	.0008952
r_18under_1arr	-.0401893	.0152803	-2.63	0.009	-.0701417	-.010237
c_age	-.0012172	.0007358	-1.65	0.098	-.0026595	.0002251
c_black	-.0050795	.0131425	-0.39	0.699	-.0308415	.0206825
c_married	-.0129221	.0167532	-0.77	0.441	-.0457617	.0199175
c_islam	-.0027379	.0146388	-0.19	0.852	-.0314329	.0259571
c_urban	-.0142175	.0121715	-1.17	0.243	-.0380761	.0096412
c_maxsent	-.0000851	.0000326	-2.61	0.009	-.0001491	-.0000212

c_cust_gt3	-.0058929	.0118802	-0.50	0.620	-.0291805	.0173946
c_misAB	.0091621	.0139465	0.66	0.511	-.0181758	.0364999
c_hadtc	-.0052533	.023121	-0.23	0.820	-.0505751	.0400684
c_ever_ac_sol	.0162921	.0160975	1.01	0.312	-.0152623	.0478464
c_3charge	-.0037543	.0095227	-0.39	0.693	-.0224208	.0149121
c_p_medlim	.0112173	.013615	0.82	0.410	-.0154708	.0379055
c_p_hsgrad	.0008409	.0121348	0.07	0.945	-.0229456	.0246275
c_p_had_job	.000766	.010888	0.07	0.944	-.0205767	.0221087
c_p_prob_drugalc	-.0012116	.0264074	-0.05	0.963	-.0529755	.0505522
c_p_prob_mh	-.0128205	.0102194	-1.25	0.210	-.0328524	.0072115
c_p_usvet	-.0257177	.0315537	-0.82	0.415	-.0875694	.0361339
c_p_iq	-.0002477	.0003317	-0.75	0.455	-.0008978	.0004024
c_18under_1arr	.0150573	.014233	1.06	0.290	-.0128422	.0429568
c_apv	.014073	.0175498	0.80	0.423	-.0203282	.0484742
c_hasPriorI	.0275772	.0135412	2.04	0.042	.0010337	.0541207
r_pri_narr	.0161879	.0018537	8.73	0.000	.0125544	.0198215
rel_pri_narr	.0010042	.0011134	0.90	0.367	-.0011782	.0031867
r_rsth	.062272	.0103331	6.03	0.000	.0420172	.0825269
rel_rsth	-.0075396	.0070226	-1.07	0.283	-.0213053	.006226
cp_age	-.0026098	.0012099	-2.16	0.031	-.0049815	-.0002381
cp_black	-.0164917	.0233791	-0.71	0.481	-.0623194	.029336
cp_married	.0166362	.0271151	0.61	0.540	-.0365148	.0697873
cp_islam	.0714407	.0284181	2.51	0.012	.0157354	.1271459
cp_urban	-.0304204	.022738	-1.34	0.181	-.0749913	.0141506
cp_maxsent	.0000554	.0000715	0.77	0.439	-.0000848	.0001955
cp_pri_narr	.0015092	.0019016	0.79	0.427	-.0022183	.0052367
cp_cust_gt3	.0048847	.0218956	0.22	0.823	-.0380351	.0478045
cp_misAB	-.0202766	.0228881	-0.89	0.376	-.0651419	.0245888
cp_hadtc	-.0219315	.0452141	-0.49	0.628	-.1105602	.0666972
cp_hasPriorI	-.0011605	.0285023	-0.04	0.968	-.0570308	.0547097
cp_ever_ac_sol	.0402279	.0261583	1.54	0.124	-.0110477	.0915035
cp_3charge	.0009657	.0193676	0.05	0.960	-.0369987	.0389302
cp_p_medlim	-.0208502	.0229005	-0.91	0.363	-.0657397	.0240393
cp_p_hsgrad	-.0147035	.0199572	-0.74	0.461	-.0538236	.0244166
cp_p_had_job	-.0236399	.019706	-1.20	0.230	-.0622676	.0149877
cp_p_prob_drugalc	-.0129707	.0331379	-0.39	0.695	-.0779277	.0519863
cp_p_prob_mh	.0146262	.0197643	0.74	0.459	-.0241159	.0533682
cp_p_usvet	.0216433	.0386637	0.56	0.576	-.0541453	.0974319
cp_p_iq	-.0002333	.0006473	-0.36	0.719	-.0015023	.0010356
cp_18under_1arr	.0119668	.0221986	0.54	0.590	-.031547	.0554806
cp_apv	.012646	.0337172	0.38	0.708	-.0534464	.0787385
stretches	-.0008389	.0046322	-0.18	0.856	-.0099189	.0082412
r_time2rel	.0000172	.00002	0.86	0.389	-.0000219	.0000563
r_staytime	-.0000253	.0000199	-1.28	0.202	-.0000643	.0000136
same_age	.0091309	.0100482	0.91	0.364	-.0105657	.0288274
same_race	.0073634	.0111928	0.66	0.511	-.0145767	.0293034
same_married	-.0111294	.0164814	-0.68	0.500	-.0434362	.0211775
same_islam	-.0179163	.0140341	-1.28	0.202	-.0454259	.0095932
same_urban	.024971	.0116503	2.14	0.032	.0021341	.0478079
same_cust_gt3	-.0161327	.0114526	-1.41	0.159	-.0385822	.0063168
same_misAB	-.0057243	.0106412	-0.54	0.591	-.0265832	.0151346
same_hadtc	-.0017078	.0223486	-0.08	0.939	-.0455156	.0421
same_ever_ac_sol	.014272	.0154397	0.92	0.355	-.0159929	.0445368
same_3charge	-.0089006	.0092224	-0.97	0.335	-.0269783	.009177
same_p_medlim	.0114058	.0133572	0.85	0.393	-.014777	.0375886
same_p_hsgrad	.0034624	.0091713	0.38	0.706	-.0145152	.02144
same_p_had_job	-.0268303	.0105926	-2.53	0.011	-.0475939	-.0060667
same_p_prob_drugalc	.0190868	.0248059	0.77	0.442	-.0295378	.0677114
same_p_prob_mh	-.0212484	.0098231	-2.16	0.031	-.0405036	-.0019933
same_p_usvet	-.0186844	.0310384	-0.60	0.547	-.0795259	.0421571
same_p_iq	-.0022969	.0089323	-0.26	0.797	-.019806	.0152122
same_18under_1arr	-.0077464	.0097967	-0.79	0.429	-.0269499	.0114571
fac_tt						
CAM	-.0237467	.0252718	-0.94	0.347	-.0732846	.0257912
CHS	-.0514059	.0346309	-1.48	0.138	-.1192893	.0164776
COA	.0167849	.0291568	0.58	0.565	-.0403684	.0739381
CRE	-.0667305	.0396828	-1.68	0.093	-.1445168	.0110557
DAL	-.0254697	.0344677	-0.74	0.460	-.0930334	.042094
FRA	.0328056	.0387304	0.85	0.397	-.0431139	.108725
FRS	-.0171347	.027294	-0.63	0.530	-.0706365	.0363671
FYT	-.0428617	.031089	-1.38	0.168	-.1038024	.018079
GRA	.0112992	.0383541	0.29	0.768	-.0638826	.086481
GRE	-.0577764	.0372267	-1.55	0.121	-.1307482	.0151954
GRN	.0047908	.039134	0.12	0.903	-.0719196	.0815013
HOU	-.0017824	.0279182	-0.06	0.949	-.0565076	.0529428
HUN	-.008776	.0361701	-0.24	0.808	-.0796767	.0621246
LAU	-.0824396	.0414062	-1.99	0.047	-.163604	-.0012752

MAH	-.0140643	.0283781	-0.50	0.620	-.069691	.0415624
MER	-.0779699	.0393495	-1.98	0.048	-.1551027	-.000837
PIT	.0318586	.0907221	0.35	0.725	-.145975	.2096922
PNG	.0299152	.0353111	0.85	0.397	-.0393017	.099132
RET	-.0293294	.0367466	-0.80	0.425	-.1013601	.0427014
ROC	-.0049769	.0318059	-0.16	0.876	-.0673228	.0573691
SMI	-.0174546	.0348607	-0.50	0.617	-.0857886	.0508794
SMR	-.0039032	.0287819	-0.14	0.892	-.0603216	.0525151
WAM	-.0140692	.0636632	-0.22	0.825	-.138862	.1107235
WAY	-.2569528	.3198512	-0.80	0.422	-.8839255	.3700199
cellsqft_tt_fa	.0004282	.0004352	0.98	0.325	-.000425	.0012813
tier_tt_fa	.022098	.0090832	2.43	0.015	.0042931	.0399028
c_time2r_tt	5.53e-06	.0001128	0.05	0.961	-.0002156	.0002267
_cons	.7105957	.1278011	5.56	0.000	.4600798	.9611115

Outcome linear probability model regression output, recidivism.

Source	SS	df	MS
Model	422.587187	115	3.67467119
Residual	1808.04552	10015	.180533752
Total	2230.63271	10130	.220200663

Number of obs = 10131
F (115, 10015) = 20.35
Prob > F = 0.0000
R-squared = 0.1894
Adj R-squared = 0.1801
Root MSE = .42489

has_post0	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
total_tt	-.0000732	.0000391	-1.87	0.061	-.0001497	3.39e-06
r_age	-.0066645	.000709	-9.40	0.000	-.0080542	-.0052747
r_black	.0414232	.0157635	2.63	0.009	.0105235	.0723229
r_married	-.0310617	.0162137	-1.92	0.055	-.0628438	.0007205
r_islam	.0542126	.0147057	3.69	0.000	.0253864	.0830388
r_urban	-.0207556	.011759	-1.77	0.078	-.0438056	.0022943
r_maxsent	-.0001386	.0001563	-0.89	0.375	-.0004451	.0001678
r_cust_gt3	.0277545	.0119556	2.32	0.020	.0043192	.0511899
r_misAB	-.0399004	.0145789	-2.74	0.006	-.068478	-.0113229
r_hadtc	.0553674	.0269758	2.05	0.040	.0024893	.1082454
r_ever_ac_sol	-.0017104	.016047	-0.11	0.915	-.0331657	.029745
r_3charge	.0189759	.0091132	2.08	0.037	.0011122	.0368395
r_p_medlim	-.0094701	.0132179	-0.72	0.474	-.0353799	.0164398
r_p_hsgrad	-.0966142	.0119878	-8.06	0.000	-.1201127	-.0731157
r_p_had_job	.0156633	.0102585	1.53	0.127	-.0044453	.035772
r_p_prob_drugalc	.00915	.0256607	0.36	0.721	-.0411502	.0594502
r_p_prob_mh	.0663752	.0100526	6.60	0.000	.0466701	.0860804
r_p_usvet	-.0283731	.0307119	-0.92	0.356	-.0885747	.0318284
r_p_iq	.0002679	.00034	0.79	0.431	-.0003986	.0009345
r_18under_1arr	-.0700941	.0147432	-4.75	0.000	-.0989938	-.0411944
c_age	-.0006734	.0007099	-0.95	0.343	-.002065	.0007182
c_black	.0017227	.0126807	0.14	0.892	-.0231339	.0265793
c_married	-.0168191	.0161644	-1.04	0.298	-.0485046	.0148663
c_islam	-.0150342	.0141243	-1.06	0.287	-.0427207	.0126523
c_urban	-.0083386	.0117438	-0.71	0.478	-.0313587	.0146815
c_maxsent	-.0000653	.0000315	-2.08	0.038	-.0001271	-3.63e-06
c_cust_gt3	-.0059399	.0114626	-0.52	0.604	-.028409	.0165292
c_misAB	-.0014651	.0134563	-0.11	0.913	-.0278422	.0249119
c_hadtc	-.0309053	.0223084	-1.39	0.166	-.0746342	.0128236
c_ever_ac_sol	.0225597	.0155318	1.45	0.146	-.0078857	.053005
c_3charge	.0087318	.009188	0.95	0.342	-.0092786	.0267422
c_p_medlim	.0011151	.0131365	0.08	0.932	-.0246351	.0268653
c_p_hsgrad	-.0032502	.0117083	-0.28	0.781	-.0262008	.0197004
c_p_had_job	-.0019509	.0105054	-0.19	0.853	-.0225436	.0186417
c_p_prob_drugalc	.0305514	.0254793	1.20	0.231	-.0193933	.080496
c_p_prob_mh	-.0053935	.0098602	-0.55	0.584	-.0247215	.0139345
c_p_usvet	-.004543	.0304448	-0.15	0.881	-.0642209	.0551348
c_p_iq	-.0002573	.00032	-0.80	0.421	-.0008846	.0003699
c_18under_1arr	-.0013629	.0137328	-0.10	0.921	-.0282818	.0255561
c_apv	.0043824	.016933	0.26	0.796	-.0288098	.0375745
c_hasPriorI	.0182161	.0130653	1.39	0.163	-.0073945	.0438267
r_pri_narr	.0135418	.0017885	7.57	0.000	.0100359	.0170476
rel_pri_narr	.0003925	.0010743	0.37	0.715	-.0017133	.0024982

r_rsth	.0705883	.0099699	7.08	0.000	.0510452	.0901313
rel_rsth	.0026806	.0067758	0.40	0.692	-.0106013	.0159624
cp_age	-.0032708	.0011674	-2.80	0.005	-.0055591	-.0009824
cp_black	-.010217	.0225574	-0.45	0.651	-.0544341	.0340001
cp_married	-.0081208	.0261621	-0.31	0.756	-.0594039	.0431622
cp_islam	.0316812	.0274194	1.16	0.248	-.0220663	.0854288
cp_urban	-.0361582	.0219388	-1.65	0.099	-.0791627	.0068464
cp_maxsent	.000035	.000069	0.51	0.612	-.0001002	.0001702
cp_pri_narr	.0024182	.0018348	1.32	0.188	-.0011783	.0060147
cp_cust_gt3	.0329769	.0211261	1.56	0.119	-.0084345	.0743883
cp_misAB	-.0171343	.0220837	-0.78	0.438	-.0604228	.0261543
cp_hadtc	-.0460849	.043625	-1.06	0.291	-.1315987	.039429
cp_hasPriorI	-.0061101	.0275006	-0.22	0.824	-.0600168	.0477966
cp_ever_ac_sol	.0363397	.025239	1.44	0.150	-.0131339	.0858132
cp_3charge	.0274607	.018687	1.47	0.142	-.0091695	.064091
cp_p_medlim	-.0186965	.0220956	-0.85	0.397	-.0620084	.0246153
cp_p_hsgrad	.0026871	.0192558	0.14	0.889	-.0350582	.0404323
cp_p_had_job	-.008663	.0190134	-0.46	0.649	-.045933	.0286071
cp_p_prob_drugalc	-.0206829	.0319733	-0.65	0.518	-.083357	.0419912
cp_p_prob_mh	-.0071339	.0190697	-0.37	0.708	-.0445143	.0302466
cp_p_usvet	.0009137	.0373049	0.02	0.980	-.0722113	.0740387
cp_p_iq	-.0002577	.0006246	-0.41	0.680	-.001482	.0009667
cp_18under_1arr	.0020334	.0214185	0.09	0.924	-.039951	.0440179
cp_apv	.0205737	.0325322	0.63	0.527	-.0431959	.0843433
stretches	-.002439	.0044694	-0.55	0.585	-.0111999	.006322
r_time2rel	-8.95e-06	.0000193	-0.46	0.642	-.0000467	.0000288
r_staytime	-.0000562	.0000192	-2.93	0.003	-.0000938	-.0000187
same_age	.0090698	.0096951	0.94	0.350	-.0099345	.0280741
same_race	.0023483	.0107994	0.22	0.828	-.0188206	.0235173
same_married	-.0161332	.0159022	-1.01	0.310	-.0473047	.0150382
same_islam	-.0252557	.0135408	-1.87	0.062	-.0517985	.001287
same_urban	.0111927	.0112408	1.00	0.319	-.0108416	.033227
same_cust_gt3	-.009587	.0110501	-0.87	0.386	-.0312475	.0120735
same_misAB	-.0013469	.0102672	-0.13	0.896	-.0214727	.018779
same_hadtc	-.0010609	.0215632	-0.05	0.961	-.0433291	.0412072
same_ever_ac_sol	.0117833	.0148971	0.79	0.429	-.017418	.0409845
same_3charge	-.0089329	.0088982	-1.00	0.315	-.0263752	.0085095
same_p_medlim	.0022591	.0128878	0.18	0.861	-.0230036	.0275217
same_p_hsgrad	.0024223	.008849	0.27	0.784	-.0149234	.019768
same_p_had_job	-.0166061	.0102203	-1.62	0.104	-.0366399	.0034277
same_p_prob_drugalc	-.0183962	.0239341	-0.77	0.442	-.0653119	.0285194
same_p_prob_mh	-.0068646	.0094778	-0.72	0.469	-.0254431	.0117138
same_p_usvet	-.006563	.0299476	-0.22	0.827	-.0652663	.0521403
same_p_iq	-.0033711	.0086184	-0.39	0.696	-.0202648	.0135226
same_18under_1arr	-.0107603	.0094524	-1.14	0.255	-.0292889	.0077683
fac_tt						
CAM	-.0275638	.0243837	-1.13	0.258	-.0753607	.0202331
CHS	-.0326285	.0334138	-0.98	0.329	-.0981262	.0328692
COA	.0328063	.0281321	1.17	0.244	-.0223383	.087951
CRE	-.0398595	.0382881	-1.04	0.298	-.114912	.0351929
DAL	-.0218343	.0332564	-0.66	0.511	-.0870235	.0433549
FRA	.0176892	.0373693	0.47	0.636	-.0555621	.0909405
FRS	-.0143358	.0263348	-0.54	0.586	-.0659573	.0372857
FYT	-.0210902	.0299964	-0.70	0.482	-.0798892	.0377088
GRA	.0352764	.0370062	0.95	0.340	-.0372632	.1078159
GRE	-.0211753	.0359184	-0.59	0.556	-.0915825	.0492319
GRN	-.0148984	.0377586	-0.39	0.693	-.0889129	.059116
HOU	.0130009	.026937	0.48	0.629	-.039801	.0658028
HUN	-.0320425	.0348989	-0.92	0.359	-.1004514	.0363664
LAU	-.0680979	.0399509	-1.70	0.088	-.1464097	.010214
MAH	.0026963	.0273807	0.10	0.922	-.0509754	.056368
MER	-.0966849	.0379665	-2.55	0.011	-.171107	-.0222629
PIT	.0182235	.0875337	0.21	0.835	-.1533602	.1898071
PNG	.0262855	.0340701	0.77	0.440	-.0404987	.0930697
RET	-.0273191	.0354552	-0.77	0.441	-.0968184	.0421801
ROC	.0086331	.0306881	0.28	0.778	-.0515218	.0687879
SMI	-.0216258	.0336355	-0.64	0.520	-.0875582	.0443065
SMR	-.0000614	.0277704	-0.00	0.998	-.0544969	.0543742
WAM	-.0469794	.0614258	-0.76	0.444	-.1673864	.0734275
WAY	-.3205088	.3086101	-1.04	0.299	-.9254467	.284429
cellsqft_tt_fa	-.00004	.0004199	-0.10	0.924	-.0008631	.0007832
tier_tt_fa	.0135601	.0087639	1.55	0.122	-.003619	.0307392
c_time2r_tt	.0001418	.0001089	1.30	0.193	-.0000716	.0003552
_cons	.8031771	.1233096	6.51	0.000	.5614656	1.044889

Chapter 9 Appendix

Conglomerate common support graphs.

Figure 9A.1: Common support of the propensity score 270-360 days.

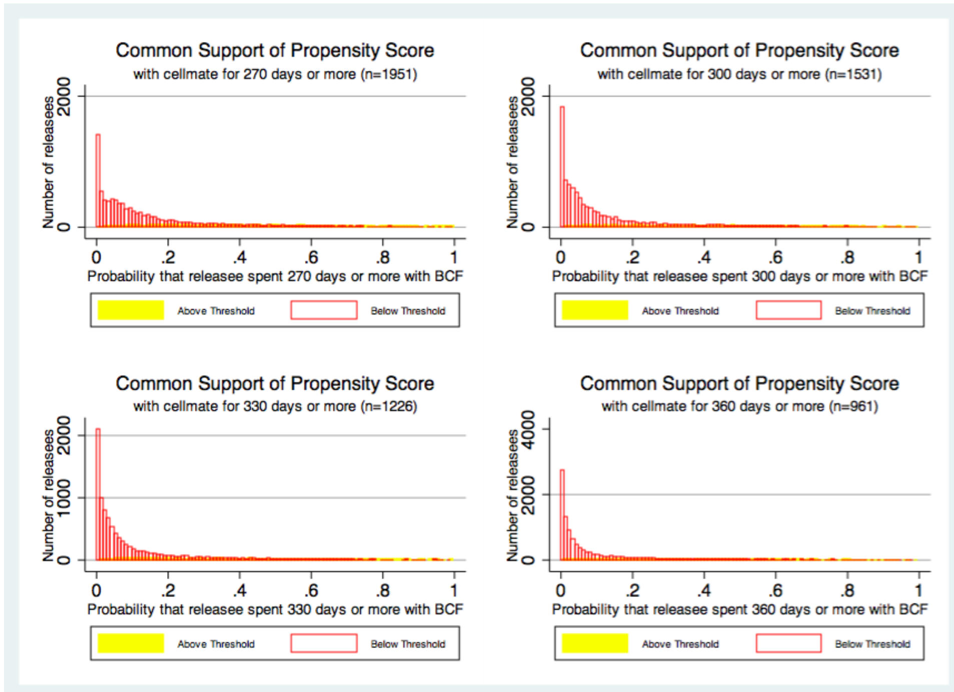


Figure 9A.2: Common support of the propensity score 290-420 days.

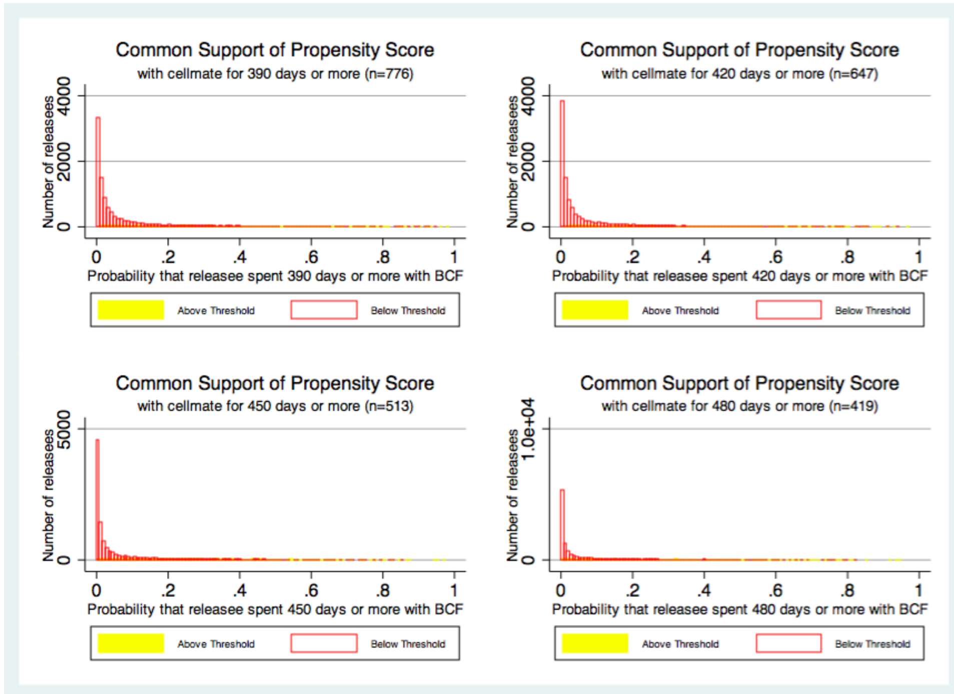


Figure 9A.3: Common support of the propensity score 510-600 days.

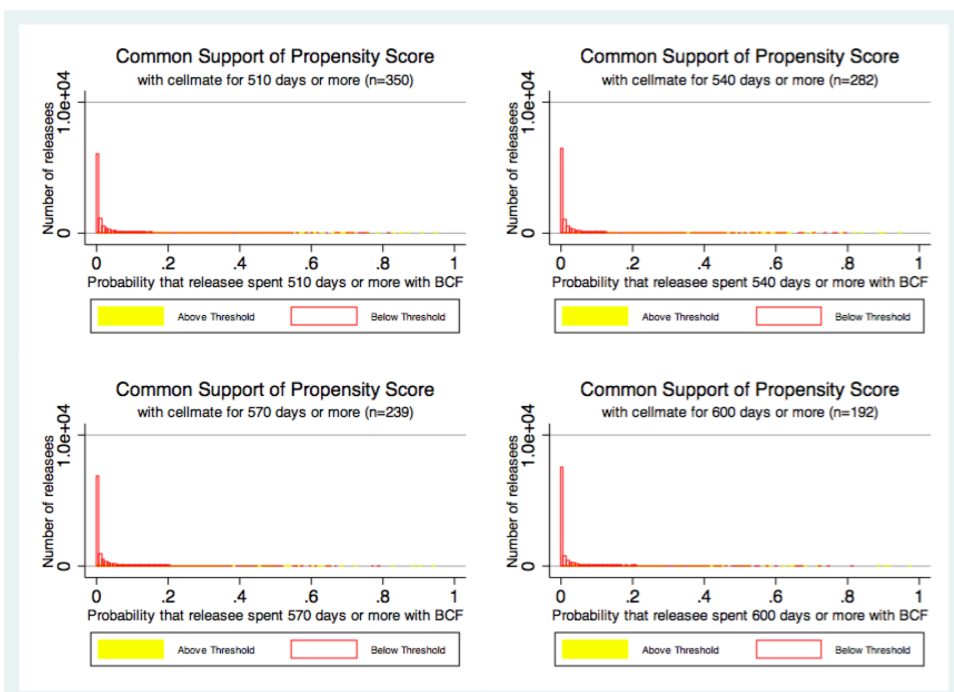
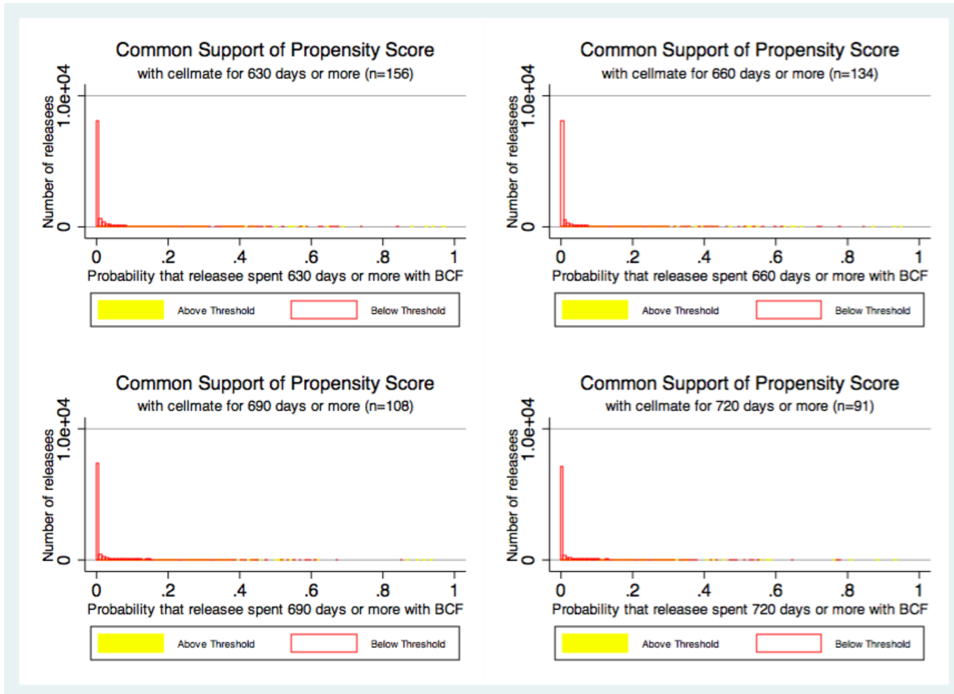


Figure 9A.4: Common support of the propensity score 630-720 days.



Example *margte* regression output.

Outcome Model #1: An example of margte Output for Rearrest.

```
Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                     Number of obs      =     10131
Treatment Model: Probit                         Replications       =        50
------------------------------------------------------------------------------
                 |   Observed   Bootstrap                         Normal-based
       has_postA |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
Treated          |
     c_hasPriorI |   .0376993    .0166013     2.27   0.023      .0051614    .0702373
      r_pri_narr |   .0252541    .0017715    14.26   0.000       .021782    .0287262
    rel_pri_narr |   .0008807     .001112     0.79   0.428     -.0012987    .0030601
           r_age |  -.0105089    .0008774   -11.98   0.000     -.0122285   -.0087893
         r_black |   .0372059    .0257656     1.44   0.149     -.0132936    .0877055
       r_married |   -.015292    .0155271    -0.98   0.325     -.0457246    .0151406
         r_islam |   .0641532    .0187518     3.42   0.001      .0274004     .100906
         r_urban |   .0302334    .0172057     1.76   0.079     -.0034892    .0639559
       r_maxsent |  -.0012622    .0002251    -5.61   0.000     -.0017034   -.0008211
     r_cust_gt3 |   .0467684     .011824     3.96   0.000      .0235937    .0699431
         r_misAB |   .0377194    .0179554     2.10   0.036      .0025274    .0729114
         r_hadtc |     .03504    .0298066     1.18   0.240     -.0233798    .0934598
    r_ever_ac_sol |  -.0015834    .0142823    -0.11   0.912     -.0295762    .0264095
       r_3charge |   .0244847    .0131129     1.87   0.062      -.001216    .0501854
       r_p_medlim |  -.0118402    .0132341    -0.89   0.371     -.0377785    .0140982
      r_p_hsgrad |  -.0159265    .0139011    -1.15   0.252     -.0431722    .0113192
      r_p_had_job |   .0690902    .0110573     6.25   0.000      .0474182    .0907622
 r_p_prob_drugalc |   .0664788    .0225092     2.95   0.003      .0223616    .1105961
      r_p_prob_mh |   .0213977     .016461     1.30   0.194     -.0108652    .0536606
       r_p_usvet |  -.0150707    .0260152    -0.58   0.562     -.0660596    .0359181
          r_p_iq |   .0001534    .0004993     0.31   0.759     -.0008251     .001132
   r_18under_1arr |   .0485798    .0159959     3.04   0.002      .0172284    .0799312
           c_age |  -.0013368    .0008487    -1.58   0.115     -.0030002    .0003267
         c_black |   .0053463    .0195206     0.27   0.784     -.0329134     .043606
       c_married |  -.0174038     .014485    -1.20   0.230     -.0457938    .0109862
         c_islam |    .008677    .0178858     0.49   0.628     -.0263785    .0437324
         c_urban |   .0002247    .0152553     0.01   0.988     -.0296751    .0301246
```

c_maxsent	-.000099	.000038	-2.61	0.009	-.0001734	-.0000246
c_cust_gt3	-.0164796	.0136991	-1.20	0.229	-.0433293	.0103701
c_misAB	.006247	.0141724	0.44	0.659	-.0215304	.0340245
c_hadtc	-.0398626	.0257054	-1.55	0.121	-.0902443	.010519
c_ever_ac_sol	.0082009	.0153014	0.54	0.592	-.0217894	.0381912
c_3charge	-.0066856	.0133327	-0.50	0.616	-.0328172	.019446
c_p_medlim	.0090317	.0149585	0.60	0.546	-.0202865	.0383498
c_p_hsgrad	-.0087261	.0122068	-0.71	0.475	-.032651	.0151989
c_p_had_job	.018007	.0115181	1.56	0.118	-.0045681	.0405821
c_p_prob_drugalc	-.0202401	.0190678	-1.06	0.288	-.0576123	.0171321
c_p_prob_mh	-.0188549	.0127836	-1.47	0.140	-.0439104	.0062005
c_p_usvet	-.0082218	.0295975	-0.28	0.781	-.0662318	.0497882
c_p_iq	-.0002305	.0003262	-0.71	0.480	-.0008698	.0004088
c_18under_1arr	.0173749	.0141874	1.22	0.221	-.0104319	.0451818
c_apv	.0044979	.0192781	0.23	0.816	-.0332865	.0422822
cp_age	-.000991	.0017145	-0.58	0.563	-.0043514	.0023693
cp_black	.0260827	.0313506	0.83	0.405	-.0353633	.0875286
cp_married	-.0412754	.0405359	-1.02	0.309	-.1207243	.0381735
cp_islam	.0430166	.0321403	1.34	0.181	-.0199774	.1060105
cp_urban	-.0427809	.0340436	-1.26	0.209	-.1095051	.0239434
cp_maxsent	.0001363	.0000773	1.76	0.078	-.0000153	.0002879
cp_pri_narr	-.0011048	.0028406	-0.39	0.697	-.0066722	.0044627
cp_cust_gt3	.0027879	.0257307	0.11	0.914	-.0476433	.0532192
cp_misAB	-.0381412	.0308258	-1.24	0.216	-.0985587	.0222762
cp_hadtc	-.0243644	.0574372	-0.42	0.671	-.1369392	.0882104
cp_hasPriorI	-.0527115	.0447689	-1.18	0.239	-.1404568	.0350338
cp_ever_ac_sol	.060071	.0318251	1.89	0.059	-.002305	.122447
cp_3charge	.022552	.0246762	0.91	0.361	-.0258124	.0709165
cp_p_medlim	-.0126715	.0354052	-0.36	0.720	-.0820644	.0567215
cp_p_hsgrad	-.0249367	.0280389	-0.89	0.374	-.0798919	.0300185
cp_p_had_job	-.0164746	.0267311	-0.62	0.538	-.0688665	.0359174
cp_p_prob_drugalc	-.0352901	.0479013	-0.74	0.461	-.1291749	.0585948
cp_p_prob_mh	.0419362	.0264442	1.59	0.113	-.0098936	.0937659
cp_p_usvet	-.0339344	.050891	-0.67	0.505	-.1336788	.0658101
cp_p_iq	-.0000735	.0009379	-0.08	0.938	-.0019117	.0017647
cp_18under_1arr	.045937	.0315037	1.46	0.145	-.0158092	.1076832
cp_apv	.0856072	.0393633	2.17	0.030	.0084565	.1627579
stretches	.0019	.004687	0.41	0.685	-.0072864	.0110865
r_time2rel	.000028	.0000204	1.37	0.171	-.0000121	.0000681
r_staytime	-.0000199	.0000249	-0.80	0.425	-.0000687	.0000289
tier_tt_fa	.0345014	.0118931	2.90	0.004	.0111915	.0578114
k	-.0375444	.0246888	-1.52	0.128	-.0859334	.0108447
_cons	.7735668	.1336496	5.79	0.000	.5116185	1.035515
Untreated						
c_hasPriorI	.0060109	.0186752	0.32	0.748	-.0305918	.0426136
r_pri_narr	.0243097	.0021162	11.49	0.000	.020162	.0284574
rel_pri_narr	.000393	.0014527	0.27	0.787	-.0024542	.0032402
r_age	-.0101561	.0008523	-11.92	0.000	-.0118265	-.0084856
r_black	.0659893	.0191706	3.44	0.001	.0284157	.103563
r_married	-.0451237	.0145559	-3.10	0.002	-.0736527	-.0165947
r_islam	.0688269	.02027	3.40	0.001	.0290984	.1085555
r_urban	.0389257	.0177713	2.19	0.028	.0040946	.0737568
r_maxsent	-.001674	.0003232	-5.18	0.000	-.0023074	-.0010405
r_cust_gt3	.0103348	.0215765	0.48	0.632	-.0319543	.0526239
r_misAB	.0405267	.0260103	1.56	0.119	-.0104525	.091506
r_hadtc	-.031245	.0540894	-0.58	0.563	-.1372583	.0747683
r_ever_ac_sol	.0227589	.0310929	0.73	0.464	-.0381821	.0837
r_3charge	.0078207	.0150537	0.52	0.603	-.021684	.0373254
r_p_medlim	-.0002649	.0205586	-0.01	0.990	-.040559	.0400292
r_p_hsgrad	-.0315499	.0165814	-1.90	0.057	-.0640488	.000949
r_p_had_job	.0722955	.0152685	4.73	0.000	.0423697	.1022213
r_p_prob_drugalc	.077479	.0219545	3.53	0.000	.0344489	.1205091
r_p_prob_mh	.0585139	.0147118	3.98	0.000	.0296793	.0873486
r_p_usvet	-.0221632	.0279223	-0.79	0.427	-.0768899	.0325634
r_p_iq	.0000437	.0005304	0.08	0.934	-.0009958	.0010832
r_18under_1arr	.0705395	.0177743	3.97	0.000	.0357024	.1053765
c_age	-.0009298	.000805	-1.16	0.248	-.0025076	.0006479
c_black	-.0141476	.0194763	-0.73	0.468	-.0523205	.0240252
c_married	.0067136	.020441	0.33	0.743	-.0333499	.0467772
c_islam	-.0057274	.0188702	-0.30	0.761	-.0427123	.0312575
c_urban	-.0197917	.0163827	-1.21	0.227	-.0519012	.0123179
c_maxsent	-.0000744	.000045	-1.65	0.098	-.0001627	.0000138
c_cust_gt3	.0298636	.0188589	1.58	0.113	-.0070992	.0668264
c_misAB	-.0062584	.0192208	-0.33	0.745	-.0439304	.0314136
c_hadtc	.0689156	.0308596	2.23	0.026	.0084319	.1293994
c_ever_ac_sol	.0087874	.0211158	0.42	0.677	-.0325988	.0501735
c_3charge	.0057188	.0115269	0.50	0.620	-.0168735	.0283111
c_p_medlim	-.0057775	.0148674	-0.39	0.698	-.0349172	.0233621
c_p_hsgrad	-.0008512	.015727	-0.05	0.957	-.0316755	.0299731
c_p_had_job	.0131016	.0111888	1.17	0.242	-.0088281	.0350313
c_p_prob_drugalc	.0378366	.0258369	1.46	0.143	-.0128027	.0884759
c_p_prob_mh	.0135556	.0129809	1.04	0.296	-.0118864	.0389977
c_p_usvet	-.0122475	.0316621	-0.39	0.699	-.0743041	.0498091
c_p_iq	-.0004174	.0004636	-0.90	0.368	-.0013259	.0004911
c_18under_1arr	.0020716	.0147888	0.14	0.889	-.0269139	.0310571
c_apv	.0193556	.0280459	0.69	0.490	-.0356133	.0743245
cp_age	-.0054125	.0017522	-3.09	0.002	-.0088467	-.0019782
cp_black	-.0636467	.0336347	-1.89	0.058	-.1295695	.002276

```
      cp_married |   .0660675   .0387329     1.71   0.088    -.0098476    .1419826
        cp_islam |   .0838049    .044631     1.88   0.060    -.0036703    .1712802
        cp_urban |   -.013968   .0323957    -0.43   0.666    -.0774624    .0495263
      cp_maxsent |  -.0000461   .0000981    -0.47   0.638    -.0002384    .0001461
     cp_pri_narr |   .0056013   .0029988     1.87   0.062    -.0002763    .0114789
     cp_cust_gt3 |   .0239819   .0336088     0.71   0.475    -.0418902     .089854
        cp_misAB |   .0011206   .0418073     0.03   0.979    -.0808201    .0830613
        cp_hadtc |  -.0086469   .0719838    -0.12   0.904    -.1497325    .1324387
    cp_hasPriorI |   .0518523   .0435744     1.19   0.234    -.0335519    .1372565
   cp_ever_ac_sol |   .0232113   .0398279     0.58   0.560      -.05485    .1012725
      cp_3charge |  -.0183468   .0273322    -0.67   0.502    -.0719169    .0352233
     cp_p_medlim |  -.0226005   .0333816    -0.68   0.498    -.0880272    .0428262
     cp_p_hsgrad |  -.0132253   .0309264    -0.43   0.669    -.0738398    .0473892
    cp_p_had_job |  -.0249173    .024914    -1.00   0.317    -.0737478    .0239131
cp_p_prob_drugalc |   -.010883   .0420232    -0.26   0.796     -.093247    .0714809
    cp_p_prob_mh |  -.0087053   .0265053    -0.33   0.743    -.0606547    .0432442
      cp_p_usvet |   .0724883   .0494917     1.46   0.143    -.0245136    .1694902
         cp_p_iq |  -.0001533   .0009625    -0.16   0.873    -.0020398    .0017332
  cp_18under_1arr |  -.0255872   .0338384    -0.76   0.450    -.0919092    .0407348
          cp_apv |  -.0630316   .0512737    -1.23   0.219    -.1635262     .037463
       stretches |  -.0152132   .0129061    -1.18   0.238    -.0405086    .0100822
      r_time2rel |   .0000601   .0000474     1.27   0.205    -.0000329    .0001531
      r_staytime |  -.0001034     .00005    -2.07   0.039    -.0002014   -5.40e-06
      tier_tt_fa |   .0107196   .0136622     0.78   0.433    -.0160578    .0374971
               k |   .0437358   .0183407     2.38   0.017     .0077886    .0796829
           _cons |   .9335556   .1540355     6.06   0.000     .6316515     1.23546
-----------------+----------------------------------------------------------------
Mills            |
       rho1-rho0 |  -.0812801   .0291741    -2.79   0.005    -.1384604   -.0240999
-----------------+----------------------------------------------------------------
ATE              |
       E(Y1-Y0)@X |   .0291465   .0267003     1.09   0.275    -.0231852    .0814781
----------------------------------------------------------------------------------
(note: file mte_base_t120_posthas_postA.gph not found)
(file mte_base_t120_posthas_postA.gph saved)
(running parametric_polynomial on estimation sample)


Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                       Number of obs      =     10131
Treatment Model: Probit                           Replications       =        50
----------------------------------------------------------------------------------
                 |   Observed   Bootstrap                         Normal-based
       has_postA |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
Treated          |
     c_hasPriorI |   .0355436   .0228216     1.56   0.119     -.009186    .0802731
      r_pri_narr |   .0257728   .0022719    11.34   0.000     .0213199    .0302257
    rel_pri_narr |   .0005424   .0013904     0.39   0.696    -.0021827    .0032676
           r_age |  -.0102214   .0010117   -10.10   0.000    -.0122043   -.0082384
         r_black |   .0375353   .0296397     1.27   0.205    -.0205575    .0956281
       r_married |   .0046441   .0208778     0.22   0.824    -.0362757    .0455638
         r_islam |   .0610649   .0179179     3.41   0.001     .0259464    .0961834
         r_urban |   .0319483    .017852     1.79   0.074    -.0030411    .0669376
       r_maxsent |  -.0012912   .0001902    -6.79   0.000     -.001664   -.0009183
      r_cust_gt3 |   .0529027   .0187316     2.82   0.005     .0161895    .0896159
         r_misAB |   .0417614   .0160236     2.61   0.009     .0103557     .073167
         r_hadtc |   .0425355    .027637     1.54   0.124     -.011632     .096703
    r_ever_ac_sol |  -.0169758   .0181711    -0.93   0.350    -.0525905     .018639
       r_3charge |   .0264627   .0114302     2.32   0.021     .0040599    .0488655
      r_p_medlim |  -.0116489   .0175825    -0.66   0.508     -.04611    .0228122
      r_p_hsgrad |  -.0119617   .0136802    -0.87   0.382    -.0387745    .0148511
     r_p_had_job |   .0674082   .0135091     4.99   0.000     .0409308    .0938856
 r_p_prob_drugalc |   .0747092   .0202985     3.68   0.000     .0349249    .1144935
     r_p_prob_mh |   .0216129    .015761     1.37   0.170     -.009278    .0525038
       r_p_usvet |  -.0385353   .0293271    -1.31   0.189    -.0960154    .0189447
          r_p_iq |  -.0001076    .000568    -0.19   0.850    -.0012208    .0010057
   r_18under_1arr |   .0462428   .0159163     2.91   0.004     .0150473    .0774383
           c_age |  -.0016948   .0009645    -1.76   0.079    -.0035851    .0001956
         c_black |  -.0066638   .0192453    -0.35   0.729    -.0443839    .0310563
       c_married |  -.0301988   .0197518    -1.53   0.126    -.0689117     .008514
         c_islam |   .0215079   .0153791     1.40   0.162    -.0086345    .0516504
         c_urban |   .0087057   .0167045     0.52   0.602    -.0240345    .0414458
       c_maxsent |   -.000098   .0000455    -2.15   0.031    -.0001873   -8.80e-06
      c_cust_gt3 |  -.0124904   .0143488    -0.87   0.384    -.0406135    .0156327
         c_misAB |   .0087772   .0151984     0.58   0.564    -.0210111    .0385656
         c_hadtc |  -.0595899   .0275079    -2.17   0.030    -.1135044   -.0056754
    c_ever_ac_sol |   -.002573   .0163492    -0.16   0.875    -.0346168    .0294708
       c_3charge |   -.009437   .0121111    -0.78   0.436    -.0331743    .0143004
      c_p_medlim |   .0129499   .0165554     0.78   0.434    -.0194981    .0453979
      c_p_hsgrad |  -.0115314   .0130383    -0.88   0.376     -.037086    .0140232
     c_p_had_job |   .0175006   .0122717     1.43   0.154    -.0065514    .0415527
 c_p_prob_drugalc |   -.029669   .0291285    -1.02   0.308    -.0867599    .0274219
     c_p_prob_mh |  -.0229631    .013532    -1.70   0.090    -.0494854    .0035591
       c_p_usvet |  -.0105445   .0375124    -0.28   0.779    -.0840675    .0629784
          c_p_iq |  -.0002266   .0005209    -0.43   0.664    -.0012474    .0007943
```

c_18under_1arr	.0102663	.0148473	0.69	0.489	-.0188339	.0393666
c_apv	.0122033	.0221427	0.55	0.582	-.0311956	.0556022
cp_age	-.0007281	.0020911	-0.35	0.728	-.0048265	.0033703
cp_black	.0295314	.0452317	0.65	0.514	-.0591211	.1181838
cp_married	-.0174681	.0462937	-0.38	0.706	-.1082021	.0732658
cp_islam	.0373234	.0442037	0.84	0.398	-.0493142	.123961
cp_urban	-.0360188	.032001	-1.13	0.260	-.0987396	.026702
cp_maxsent	.0001179	.0001089	1.08	0.279	-.0000955	.0003313
cp_pri_narr	-.0007402	.0027763	-0.27	0.790	-.0061816	.0047012
cp_cust_gt3	-.0094236	.032229	-0.29	0.770	-.0725912	.053744
cp_misAB	-.0519464	.03609	-1.44	0.150	-.1226816	.0187887
cp_hadtc	-.0463427	.0664719	-0.70	0.486	-.1766252	.0839399
cp_hasPriorI	-.0603852	.0506174	-1.19	0.233	-.1595934	.038823
cp_ever_ac_sol	.0687524	.0379689	1.81	0.070	-.0056652	.14317
cp_3charge	.0331923	.0282457	1.18	0.240	-.0221682	.0885528
cp_p_medlim	-.0032747	.0310987	-0.11	0.916	-.0642271	.0576777
cp_p_hsgrad	-.0280034	.0291245	-0.96	0.336	-.0850863	.0290795
cp_p_had_job	-.0456752	.0277236	-1.65	0.099	-.1000124	.0086619
cp_p_prob_drugalc	-.0262075	.052286	-0.50	0.616	-.1286861	.0762711
cp_p_prob_mh	.0471157	.0267226	1.76	0.078	-.0052596	.0994909
cp_p_usvet	-.00128	.0664119	-0.02	0.985	-.1314449	.1288849
cp_p_iq	.0003646	.0011401	0.32	0.749	-.0018699	.002599
cp_18under_1arr	.0683465	.0366968	1.86	0.063	-.0035778	.1402709
cp_apv	.0857291	.0552284	1.55	0.121	-.0225166	.1939749
stretches	.0036872	.0051752	0.71	0.476	-.0064559	.0138303
r_time2rel	.0000252	.0000236	1.07	0.286	-.0000211	.0000715
r_staytime	-3.16e-06	.0000219	-0.14	0.885	-.000046	.0000397
tier_tt_fa	.0373776	.011931	3.13	0.002	.0139932	.0607619
k	-.0407878	.0239431	-1.70	0.088	-.0877154	.0061399
_cons	.7046799	.1657616	4.25	0.000	.3797932	1.029567
Untreated						
c_hasPriorI	.0164724	.020869	0.79	0.430	-.0244301	.0573749
r_pri_narr	.0239208	.0017482	13.68	0.000	.0204944	.0273472
rel_pri_narr	.0008417	.0011732	0.72	0.473	-.0014577	.0031412
r_age	-.0104321	.0008674	-12.03	0.000	-.0121322	-.008732
r_black	.0654629	.0159493	4.10	0.000	.0342029	.096723
r_married	-.0571803	.0202115	-2.83	0.005	-.0967941	-.0175666
r_islam	.06978	.0192167	3.63	0.000	.032116	.1074439
r_urban	.0380516	.0134004	2.84	0.005	.0117872	.0643159
r_maxsent	-.0015279	.0003178	-4.81	0.000	-.0021508	-.000905
r_cust_gt3	.01146	.018425	0.62	0.534	-.0246522	.0475723
r_misAB	.0365343	.0213412	1.71	0.087	-.0052937	.0783623
r_hadtc	-.0072139	.0505509	-0.14	0.887	-.1062918	.091864
r_ever_ac_sol	.0364751	.0246143	1.48	0.138	-.0117681	.0847182
r_3charge	.0114598	.0161619	0.71	0.478	-.020217	.0431366
r_p_medlim	-.0048021	.0185175	-0.26	0.795	-.0410958	.0314916
r_p_hsgrad	-.0322838	.0146833	-2.20	0.028	-.0610625	-.0035051
r_p_had_job	.0724132	.0137454	5.27	0.000	.0454727	.0993537
r_p_prob_drugalc	.0629996	.0249822	2.52	0.012	.0140353	.1119639
r_p_prob_mh	.0526099	.0143701	3.66	0.000	.024445	.0807748
r_p_usvet	.0026382	.0267047	0.10	0.921	-.049702	.0549785
r_p_iq	.0003268	.000405	0.81	0.420	-.000467	.0011205
r_18under_1arr	.066662	.0147776	4.51	0.000	.0376984	.0956255
c_age	-.0008113	.0007844	-1.03	0.301	-.0023487	.0007262
c_black	-.0014575	.0158356	-0.09	0.927	-.0324948	.0295798
c_married	.0168	.0202862	0.83	0.408	-.0229602	.0565603
c_islam	-.0153367	.0166684	-0.92	0.358	-.0480062	.0173328
c_urban	-.0225648	.0153685	-1.47	0.142	-.0526866	.0075569
c_maxsent	-.0000716	.0000352	-2.03	0.042	-.0001405	-2.61e-06
c_cust_gt3	.0180855	.0153476	1.18	0.239	-.0119952	.0481663
c_misAB	-.005747	.017125	-0.34	0.737	-.0393115	.0278175
c_hadtc	.0681523	.028923	2.36	0.018	.0114642	.1248404
c_ever_ac_sol	.0222915	.0177119	1.26	0.208	-.0124232	.0570062
c_3charge	.004485	.0123694	0.36	0.717	-.0197585	.0287285
c_p_medlim	-.0051595	.0180721	-0.29	0.775	-.0405802	.0302612
c_p_hsgrad	-.0031849	.0115361	-0.28	0.782	-.0257953	.0194255
c_p_had_job	.0132945	.0119063	1.12	0.264	-.0100415	.0366304
c_p_prob_drugalc	.0380118	.0288345	1.32	0.187	-.0185028	.0945265
c_p_prob_mh	.0104751	.0126113	0.83	0.406	-.0142426	.0351929
c_p_usvet	-.0061351	.0239532	-0.26	0.798	-.0530826	.0408123
c_p_iq	-.0003648	.0004547	-0.80	0.422	-.0012559	.0005264
c_18under_1arr	.0109865	.014665	0.75	0.454	-.0177563	.0397294
c_apv	.0060521	.0234978	0.26	0.797	-.0400028	.0521069
cp_age	-.0049394	.0015422	-3.20	0.001	-.007962	-.0019168
cp_black	-.0521749	.0259193	-2.01	0.044	-.1029758	-.001374
cp_married	.0375994	.0397934	0.94	0.345	-.0403942	.1155931
cp_islam	.0829387	.0421978	1.97	0.049	.0002325	.1656449
cp_urban	-.0199092	.0315319	-0.63	0.528	-.0817105	.0418922
cp_maxsent	1.80e-06	.0000754	0.02	0.981	-.000146	.0001497
cp_pri_narr	.004065	.0027383	1.48	0.138	-.001302	.009432
cp_cust_gt3	.0320699	.0351077	0.91	0.361	-.03674	.1008798
cp_misAB	.0046197	.0346149	0.13	0.894	-.0632243	.0724636
cp_hadtc	-.0095717	.0694301	-0.14	0.890	-.1456521	.1265087
cp_hasPriorI	.0414264	.0364974	1.14	0.256	-.0301073	.11296
cp_ever_ac_sol	.0232569	.037668	0.62	0.537	-.0505711	.0970849
cp_3charge	-.025794	.0254279	-1.01	0.310	-.0756318	.0240438
cp_p_medlim	-.027227	.0369704	-0.74	0.461	-.0996877	.0452337
cp_p_hsgrad	-.0108081	.0258697	-0.42	0.676	-.0615117	.0398955

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     cp_p_had_job |  -.0012481   .0254513    -0.05   0.961    -.0511317    .0486354
cp_p_prob_drugalc |  -.0205132    .046148    -0.44   0.657    -.1109616    .0699351
    cp_p_prob_mh |  -.0070262   .0262715    -0.27   0.789    -.0585174     .044465
       cp_p_usvet |   .0335383   .0449975     0.75   0.456    -.0546551    .1217318
          cp_p_iq |  -.0002836   .0006513    -0.44   0.663    -.0015601    .0009929
  cp_18under_1arr |  -.0263158   .0288101    -0.91   0.361    -.0827826     .030151
           cp_apv |  -.0373002    .047519    -0.78   0.432    -.1304357    .0558353
        stretches |  -.0171923   .0121481    -1.42   0.157    -.0410023    .0066176
       r_time2rel |   .0000339   .0000445     0.76   0.447    -.0000534    .0001211
       r_staytime |   -.000083   .0000463    -1.79   0.073    -.0001738    7.84e-06
       tier_tt_fa |   .0144653   .0081864     1.77   0.077    -.0015798    .0305104
                k |   .0409424   .0222549     1.84   0.066    -.0026763    .0845611
            _cons |   .9318097    .127094     7.33   0.000     .6827099    1.180909
------------------+----------------------------------------------------------------
Mills             |
        rho1-rho0 |  -.0817302   .0309232    -2.64   0.008    -.1423385   -.0211219
------------------+----------------------------------------------------------------
ATE               |
        E(Y1-Y0)@X |  -.0010626   .0314647    -0.03   0.973    -.0627324    .0606072
-----------------------------------------------------------------------------------
(note: file mte_base_t150_posthas_postA.gph not found)
(file mte_base_t150_posthas_postA.gph saved)
(running parametric_polynomial on estimation sample)

Bootstrap replications (50)

Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                     Number of obs      =     10131
Treatment Model: Probit                         Replications       =        50
-----------------------------------------------------------------------------------
                  |   Observed   Bootstrap                         Normal-based
        has_postA |      Coef.   Std. Err.       z    P>|z|     [95% Conf. Interval]
------------------+----------------------------------------------------------------
Treated           |
      c_hasPriorI |   .0308928   .0207996     1.49   0.137    -.0098738    .0716593
       r_pri_narr |   .0263447   .0021784    12.09   0.000     .0220752    .0306143
     rel_pri_narr |    .001009    .001424     0.71   0.479    -.0017819    .0037999
            r_age |  -.0106964   .0010273   -10.41   0.000    -.0127098    -.008683
          r_black |   .0303002   .0358631     0.84   0.398    -.0399901    .1005906
        r_married |  -.0014247   .0220318    -0.06   0.948    -.0446063    .0417569
          r_islam |   .0606002   .0214867     2.82   0.005      .018487    .1027134
          r_urban |   .0331253   .0196121     1.69   0.091    -.0053137    .0715644
        r_maxsent |  -.0013578   .0002081    -6.53   0.000    -.0017657    -.00095
       r_cust_gt3 |   .0593873   .0213108     2.79   0.005     .0176188    .1011557
          r_misAB |   .0481901   .0145446     3.31   0.001     .0196832    .0766971
          r_hadtc |   .0436734   .0342644     1.27   0.202    -.0234836    .1108303
    r_ever_ac_sol |  -.0010036   .0213226    -0.05   0.962    -.0427951    .0407878
        r_3charge |   .0453758   .0135213     3.36   0.001     .0188745     .071877
        r_p_medlim |   .0039813   .0174007     0.23   0.819    -.0301234     .038086
       r_p_hsgrad |   -.015316   .0172789    -0.89   0.375     -.049182      .01855
     r_p_had_job |   .0706511   .0168546     4.19   0.000     .0376167    .1036854
 r_p_prob_drugalc |   .0594389   .0290681     2.04   0.041     .0024664    .1164113
     r_p_prob_mh |   .0163535   .0161218     1.01   0.310    -.0152446    .0479516
       r_p_usvet |  -.0256337   .0274279    -0.93   0.350    -.0793914    .0281241
          r_p_iq |  -.0001567   .0006165    -0.25   0.799     -.001365    .0010516
   r_18under_1arr |   .0508304   .0176892     2.87   0.004     .0161602    .0855006
            c_age |  -.0022949   .0011364    -2.02   0.043    -.0045223   -.0000676
          c_black |  -.0134873   .0235017    -0.57   0.566    -.0595498    .0325752
        c_married |  -.0347124   .0219334    -1.58   0.114     -.077701    .0082762
          c_islam |   .0198505   .0223085     0.89   0.374    -.0238733    .0635743
          c_urban |   .0212668   .0203548     1.04   0.296    -.0186279    .0611614
        c_maxsent |  -.0000302     .00004    -0.76   0.450    -.0001086    .0000482
       c_cust_gt3 |  -.0122376   .0169993    -0.72   0.472    -.0455556    .0210804
          c_misAB |   .0039935   .0174641     0.23   0.819    -.0302355    .0382225
          c_hadtc |  -.0554598   .0314389    -1.76   0.078     -.117079    .0061594
    c_ever_ac_sol |  -.0191135    .020332    -0.94   0.347    -.0589634    .0207364
        c_3charge |  -.0035689    .016078    -0.22   0.824    -.0350813    .0279435
       c_p_medlim |   .0087411   .0154775     0.56   0.572    -.0215944    .0390765
       c_p_hsgrad |  -.0074633    .016199    -0.46   0.645    -.0392127    .0242862
     c_p_had_job |   .0146619   .0170494     0.86   0.390    -.0187543     .048078
 c_p_prob_drugalc |  -.0198782   .0251893    -0.79   0.430    -.0692484     .029492
     c_p_prob_mh |  -.0089913   .0119332    -0.75   0.451    -.0323799    .0143973
       c_p_usvet |  -.0114872   .0285582    -0.40   0.688    -.0674602    .0444858
          c_p_iq |  -.0000951   .0006045    -0.16   0.875    -.0012799    .0010897
   c_18under_1arr |  -.0043975   .0155112    -0.28   0.777    -.0347989    .0260039
            c_apv |   .0039049   .0264841     0.15   0.883    -.0480029    .0558127
           cp_age |  -.0001527   .0022136    -0.07   0.945    -.0044913    .0041859
         cp_black |   .0320061   .0410581     0.78   0.436    -.0484663    .1124785
       cp_married |  -.0325486   .0488271    -0.67   0.505     -.128248    .0631508
         cp_islam |   .0554007   .0438925     1.26   0.207    -.0306271    .1414285
         cp_urban |   -.038941   .0416558    -0.93   0.350    -.1205849    .0427029
       cp_maxsent |   .0001797   .0001235     1.45   0.146    -.0000624    .0004218
      cp_pri_narr |   .0006033   .0034473     0.17   0.861    -.0061534    .0073599
      cp_cust_gt3 |  -.0217989    .040332    -0.54   0.589    -.1008481    .0572503
         cp_misAB |  -.0430412   .0379935    -1.13   0.257     -.117507    .0314247
         cp_hadtc |  -.0596267   .0652207    -0.91   0.361     -.187457    .0682036
```

cp_hasPriorI	-.0647362	.0491261	-1.32	0.188	-.1610216	.0315492
cp_ever_ac_sol	.0649077	.0370786	1.75	0.080	-.0077649	.1375803
cp_3charge	.0293867	.0323586	0.91	0.364	-.034035	.0928084
cp_p_medlim	-.0160355	.034397	-0.47	0.641	-.0834523	.0513813
cp_p_hsgrad	-.0242643	.034192	-0.71	0.478	-.0912793	.0427507
cp_p_had_job	-.0479557	.0327757	-1.46	0.143	-.1121949	.0162835
cp_p_prob_drugalc	-.0536808	.0583074	-0.92	0.357	-.1679612	.0605996
cp_p_prob_mh	.0484631	.0334885	1.45	0.148	-.0171733	.1140994
cp_p_usvet	.0541863	.0604736	0.90	0.370	-.0643399	.1727124
cp_p_iq	7.67e-06	.0013149	0.01	0.995	-.0025695	.0025849
cp_18under_1arr	.0759888	.0363784	2.09	0.037	.0046886	.1472891
cp_apv	.0711697	.0624639	1.14	0.255	-.0512572	.1935966
stretches	.0015104	.0060936	0.25	0.804	-.0104328	.0134537
r_time2rel	.0000297	.000022	1.35	0.177	-.0000135	.000073
r_staytime	-3.01e-06	.0000255	-0.12	0.906	-.0000531	.000047
tier_tt_fa	.0424039	.0126249	3.36	0.001	.0176595	.0671482
k	-.0300693	.0263026	-1.14	0.253	-.0816216	.0214829
_cons	.7290755	.1814755	4.02	0.000	.37339	1.084761
Untreated						
c_hasPriorI	.0244773	.0202802	1.21	0.227	-.0152711	.0642257
r_pri_narr	.0241361	.0022186	10.88	0.000	.0197877	.0284845
rel_pri_narr	.0006144	.0012117	0.51	0.612	-.0017604	.0029893
r_age	-.0102077	.0008792	-11.61	0.000	-.0119309	-.0084844
r_black	.0676242	.0194185	3.48	0.000	.0295645	.1056838
r_married	-.0406673	.017238	-2.36	0.018	-.0744533	-.0068814
r_islam	.0676838	.0161311	4.20	0.000	.0360674	.0993002
r_urban	.0333696	.0137319	2.43	0.015	.0064556	.0602836
r_maxsent	-.0014466	.0002531	-5.72	0.000	-.0019426	-.0009506
r_cust_gt3	.0176983	.012622	1.40	0.161	-.0070403	.0424369
r_misAB	.0281893	.0178974	1.58	0.115	-.0068889	.0632675
r_hadtc	-.0105978	.0343323	-0.31	0.758	-.077888	.0566923
r_ever_ac_sol	.0153247	.022752	0.67	0.501	-.0292683	.0599177
r_3charge	.0005539	.0103477	0.05	0.957	-.0197273	.0208351
r_p_medlim	-.016229	.0186346	-0.87	0.384	-.0527521	.0202941
r_p_hsgrad	-.0276583	.0130896	-2.11	0.035	-.0533134	-.0020031
r_p_had_job	.0707863	.012395	5.71	0.000	.0464925	.0950801
r_p_prob_drugalc	.0761335	.0230016	3.31	0.001	.0310512	.1212158
r_p_prob_mh	.0528562	.0114073	4.63	0.000	.0304982	.0752142
r_p_usvet	-.0110777	.0246429	-0.45	0.653	-.059377	.0372215
r_p_iq	.0002521	.0004094	0.62	0.538	-.0005504	.0010545
r_18under_1arr	.0607951	.016214	3.75	0.000	.0290162	.092574
c_age	-.0006081	.0009487	-0.64	0.522	-.0024675	.0012513
c_black	.0009803	.0126443	0.08	0.938	-.0238021	.0257627
c_married	.0124098	.0164257	0.76	0.450	-.019784	.0446036
c_islam	-.0086105	.013971	-0.62	0.538	-.0359933	.0187722
c_urban	-.0245324	.0132993	-1.84	0.065	-.0505986	.0015339
c_maxsent	-.0001274	.0000476	-2.68	0.007	-.0002206	-.0000342
c_cust_gt3	.0160073	.0124037	1.29	0.197	-.0083036	.0403182
c_misAB	-.0013175	.0143761	-0.09	0.927	-.0294942	.0268591
c_hadtc	.0372279	.0274509	1.36	0.175	-.0165749	.0910308
c_ever_ac_sol	.0315816	.0164728	1.92	0.055	-.0007044	.0638676
c_3charge	-.0015915	.0131966	-0.12	0.904	-.0274564	.0242734
c_p_medlim	.0025717	.0131364	0.20	0.845	-.0231751	.0283186
c_p_hsgrad	-.0041471	.0116734	-0.36	0.722	-.0270266	.0187325
c_p_had_job	.0154837	.0119528	1.30	0.195	-.0079434	.0389108
c_p_prob_drugalc	.0224291	.0220117	1.02	0.308	-.0207131	.0655712
c_p_prob_mh	-.0040212	.0130266	-0.31	0.758	-.0295529	.0215104
c_p_usvet	-.0077526	.0251915	-0.31	0.758	-.057127	.0416218
c_p_iq	-.0004684	.0004118	-1.14	0.255	-.0012756	.0003387
c_18under_1arr	.0195443	.0133239	1.47	0.142	-.0065701	.0456586
c_apv	.0083032	.0167581	0.50	0.620	-.0245421	.0411484
cp_age	-.0047088	.0013617	-3.46	0.001	-.0073777	-.0020398
cp_black	-.0426132	.0356704	-1.19	0.232	-.112526	.0272996
cp_married	.0350412	.028367	1.24	0.217	-.020557	.0906395
cp_islam	.0646791	.0379554	1.70	0.088	-.0097121	.1390702
cp_urban	-.0202706	.0308814	-0.66	0.512	-.0807971	.0402559
cp_maxsent	-.0000281	.0000932	-0.30	0.763	-.0002107	.0001546
cp_pri_narr	.0027838	.0021228	1.31	0.190	-.0013768	.0069443
cp_cust_gt3	.029733	.0259454	1.15	0.252	-.0211191	.0805851
cp_misAB	-.01249	.0316269	-0.39	0.693	-.0744777	.0494977
cp_hadtc	.0055286	.0586458	0.09	0.925	-.1094151	.1204723
cp_hasPriorI	.0337271	.0383456	0.88	0.379	-.0414289	.1088832
cp_ever_ac_sol	.0278742	.0283596	0.98	0.326	-.0277097	.083458
cp_3charge	-.0176615	.0249401	-0.71	0.479	-.0665431	.0312201
cp_p_medlim	-.0149185	.0306341	-0.49	0.626	-.0749602	.0451232
cp_p_hsgrad	-.015186	.0251892	-0.60	0.547	-.0645559	.034184
cp_p_had_job	.0003744	.0233112	0.02	0.987	-.0453146	.0460634
cp_p_prob_drugalc	-.0053015	.0411953	-0.13	0.898	-.0860428	.0754398
cp_p_prob_mh	-.0037998	.0233129	-0.16	0.871	-.0494923	.0418926
cp_p_usvet	.0051228	.0463349	0.11	0.912	-.085692	.0959376
cp_p_iq	-.0000715	.0007818	-0.09	0.927	-.0016038	.0014607
cp_18under_1arr	-.0175902	.0244643	-0.72	0.472	-.0655395	.030359
cp_apv	-.0101072	.0469693	-0.22	0.830	-.1021654	.0819511
stretches	-.0107871	.008976	-1.20	0.229	-.0283797	.0068056
r_time2rel	.00003	.0000285	1.05	0.293	-.0000259	.0000859
r_staytime	-.0000812	.0000344	-2.36	0.018	-.0001487	-.0000138
tier_tt_fa	.013599	.0119581	1.14	0.255	-.0098384	.0370364
k	.0621536	.0270078	2.30	0.021	.0092192	.115088

```
           _cons |   .9032531   .1406434     6.42   0.000     .6275971    1.178909
-----------------+----------------------------------------------------------------
Mills            |
       rho1-rho0 |  -.0922229   .0370261    -2.49   0.013    -.1647928   -.0196531
-----------------+----------------------------------------------------------------
ATE              |
      E(Y1-Y0)@X |  -.0109758   .0315665    -0.35   0.728     -.072845    .0508933
----------------------------------------------------------------------------------
(note: file mte_base_t180_posthas_postA.gph not found)
(file mte_base_t180_posthas_postA.gph saved)
(running parametric_polynomial on estimation sample)
```

Outcome Model #1: An example of margte Output for Recidivism.

```
 (running parametric_normal on estimation sample)

Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                      Number of obs      =     10131
Treatment Model: Probit                          Replications       =        50
----------------------------------------------------------------------------------
                 |   Observed   Bootstrap                         Normal-based
      has_post0  |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
Treated          |
      c_hasPriorI |   .0271904      .0158     1.72   0.085    -.0037771    .0581579
       r_pri_narr |   .0232926   .0015613    14.92   0.000     .0202325    .0263528
     rel_pri_narr |   .0006598   .0010497     0.63   0.530    -.0013976    .0027171
            r_age |  -.0103567   .0008709   -11.89   0.000    -.0120636   -.0086499
          r_black |   .0267587   .0218598     1.22   0.221    -.0160857    .0696031
        r_married |   -.011117   .0169838    -0.65   0.513    -.0444046    .0221705
          r_islam |   .0663891   .0178204     3.73   0.000     .0314617    .1013166
          r_urban |  -.0193001   .0149845    -1.29   0.198    -.0486691     .010069
        r_maxsent |  -.0002347   .0002008    -1.17   0.243    -.0006283     .000159
      r_cust_gt3 |   .0451502   .0152961     2.95   0.003     .0151703    .0751301
          r_misAB |   .0266904   .0153076     1.74   0.081     -.003312    .0566927
          r_hadtc |    .073114   .0256308     2.85   0.004     .0228785    .1233495
    r_ever_ac_sol |   -.012348   .0179798    -0.69   0.492    -.0475877    .0228918
        r_3charge |   .0143461   .0116043     1.24   0.216     -.008398    .0370902
        r_p_medlim |  -.0191508    .013601    -1.41   0.159    -.0458084    .0075067
       r_p_hsgrad |  -.0293052    .012328    -2.38   0.017    -.0534675   -.0051428
      r_p_had_job |   .0254964   .0136914     1.86   0.063    -.0013382    .0523309
  r_p_prob_drugalc |   .0775446   .0212054     3.66   0.000     .0359828    .1191065
      r_p_prob_mh |   .0634179   .0117565     5.39   0.000     .0403756    .0864602
        r_p_usvet |  -.0244081   .0299796    -0.81   0.416    -.0831669    .0343508
           r_p_iq |   .0004574   .0004568     1.00   0.317    -.0004378    .0013526
   r_18under_1arr |   .0205043   .0131862     1.55   0.120    -.0053401    .0463487
            c_age |  -.0009612   .0009435    -1.02   0.308    -.0028105    .0008881
          c_black |   .0159131   .0189852     0.84   0.402    -.0212971    .0531234
        c_married |  -.0154577   .0183384    -0.84   0.399    -.0514002    .0204848
          c_islam |   -.010591   .0160909    -0.66   0.510    -.0421286    .0209466
          c_urban |  -.0039638   .0136298    -0.29   0.771    -.0306776      .02275
        c_maxsent |  -.0000843   .0000364    -2.32   0.020    -.0001556    -.000013
       c_cust_gt3 |  -.0103409   .0130363    -0.79   0.428    -.0358915    .0152097
          c_misAB |   .0137587   .0126518     1.09   0.277    -.0110383    .0385557
          c_hadtc |  -.0563635   .0200643    -2.81   0.005    -.0956888   -.0170382
    c_ever_ac_sol |   .0101756   .0110753     0.92   0.358    -.0115317    .0318828
        c_3charge |   .0073526   .0104922     0.70   0.483    -.0132118     .027917
       c_p_medlim |    -.000554   .0149487    -0.04   0.970    -.0298528    .0287449
       c_p_hsgrad |   .0075631   .0131692     0.57   0.566     -.018248    .0333743
      c_p_had_job |   .0082644   .0118935     0.69   0.487    -.0150465    .0315753
  c_p_prob_drugalc |   .0072794   .0180501     0.40   0.687    -.0280982     .042657
      c_p_prob_mh |  -.0080115   .0125683    -0.64   0.524    -.0326448    .0166219
        c_p_usvet |   .0088094   .0239494     0.37   0.713    -.0381306    .0557495
           c_p_iq |  -.0006358   .0004423    -1.44   0.151    -.0015027    .0002312
   c_18under_1arr |   .0141633   .0118284     1.20   0.231    -.0090199    .0373465
            c_apv |    -.000498   .0188692    -0.03   0.979     -.037481     .036485
           cp_age |  -.0025304    .001934    -1.31   0.191    -.0063211    .0012602
         cp_black |   .0235693   .0312955     0.75   0.451    -.0377688    .0849074
       cp_married |  -.0460874   .0368618    -1.25   0.211    -.1183352    .0261604
         cp_islam |   .0025674   .0371884     0.07   0.945    -.0703205    .0754552
         cp_urban |  -.0199066    .028136    -0.71   0.479    -.0750522    .0352389
       cp_maxsent |    .000084   .0000846     0.99   0.320    -.0000817    .0002498
      cp_pri_narr |   .0001302   .0023663     0.06   0.956    -.0045077    .0047681
      cp_cust_gt3 |     .04512   .0338458     1.33   0.182    -.0212166    .1114567
         cp_misAB |  -.0347815   .0320605    -1.08   0.278    -.0976189     .028056
         cp_hadtc |  -.0563145   .0547932    -1.03   0.304    -.1637071    .0510781
     cp_hasPriorI |  -.0337687   .0397278    -0.85   0.395    -.1116337    .0440963
   cp_ever_ac_sol |    .039217   .0369417     1.06   0.288    -.0331874    .1116213
       cp_3charge |   .0392983   .0269219     1.46   0.144    -.0134675    .0920642
      cp_p_medlim |    -.027603   .0341374    -0.81   0.419    -.0945111    .0393052
      cp_p_hsgrad |  -.0049697   .0283356    -0.18   0.861    -.0605064     .050567
     cp_p_had_job |   .0025727   .0258944     0.10   0.921    -.0481794    .0533248
```

cp_p_prob_drugalc	-.0373831	.0419744	-0.89	0.373	-.1196514	.0448853
cp_p_prob_mh	.0107806	.0262395	0.41	0.681	-.0406479	.062209
cp_p_usvet	-.0616655	.0624821	-0.99	0.324	-.184128	.0607971
cp_p_iq	.000118	.0010764	0.11	0.913	-.0019916	.0022276
cp_18under_1arr	.0220452	.029714	0.74	0.458	-.036193	.0802835
cp_apv	.071019	.0458583	1.55	0.121	-.0188617	.1608996
stretches	-.00323	.0049787	-0.65	0.516	-.0129881	.0065281
r_time2rel	3.91e-06	.0000219	0.18	0.858	-.000039	.0000468
r_staytime	-.00005	.0000215	-2.32	0.020	-.0000921	-7.84e-06
tier_tt_fa	.0253578	.0119361	2.12	0.034	.0019634	.0487522
k	-.0118904	.0239777	-0.50	0.620	-.0588858	.035105
_cons	.8807975	.1286447	6.85	0.000	.6286586	1.132936
Untreated						
c_hasPriorI	-.0034097	.0191952	-0.18	0.859	-.0410315	.0342122
r_pri_narr	.0225747	.0021339	10.58	0.000	.0183923	.0267571
rel_pri_narr	.0015354	.0015119	1.02	0.310	-.0014278	.0044987
r_age	-.0106924	.0009245	-11.57	0.000	-.0125043	-.0088805
r_black	.0502477	.0187641	2.68	0.007	.0134709	.0870246
r_married	-.0459967	.0181414	-2.54	0.011	-.0815531	-.0104403
r_islam	.062805	.0205398	3.06	0.002	.0225477	.1030624
r_urban	-.0044009	.0160398	-0.27	0.784	-.0358383	.0270365
r_maxsent	-.0003058	.0003473	-0.88	0.379	-.0009866	.0003749
r_cust_gt3	.0157937	.0173295	0.91	0.362	-.0181715	.049759
r_misAB	.0483608	.0249122	1.94	0.052	-.0004663	.0971878
r_hadtc	-.0201925	.0497623	-0.41	0.685	-.1177247	.0773397
r_ever_ac_sol	.0271702	.0267612	1.02	0.310	-.0252808	.0796213
r_3charge	.0198073	.014179	1.40	0.162	-.007983	.0475976
r_p_medlim	.0039153	.0197587	0.20	0.843	-.034811	.0426416
r_p_hsgrad	-.0300653	.0108054	-2.78	0.005	-.0512435	-.0088872
r_p_had_job	.0075603	.0151638	0.50	0.618	-.0221602	.0372808
r_p_prob_drugalc	.0682165	.0296646	2.30	0.021	.0100749	.1263581
r_p_prob_mh	.0869203	.0168441	5.16	0.000	.0539063	.1199342
r_p_usvet	-.0134395	.0374864	-0.36	0.720	-.0869115	.0600326
r_p_iq	-.0002771	.0004392	-0.63	0.528	-.001138	.0005837
r_18under_1arr	.0344619	.0188864	1.82	0.068	-.0025547	.0714785
c_age	-.0013656	.0008656	-1.58	0.115	-.0030623	.000331
c_black	-.0109756	.0223287	-0.49	0.623	-.0547389	.0327878
c_married	.0004443	.0177753	0.02	0.980	-.0343947	.0352834
c_islam	.0027278	.0245508	0.11	0.912	-.045391	.0508466
c_urban	-.0086248	.0186351	-0.46	0.643	-.0451489	.0278992
c_maxsent	-.0000351	.0000508	-0.69	0.489	-.0001347	.0000645
c_cust_gt3	.0129384	.0144486	0.90	0.371	-.0153803	.0412572
c_misAB	-.01707	.0186542	-0.92	0.360	-.0536316	.0194916
c_hadtc	.0302594	.0352453	0.86	0.391	-.0388202	.0993389
c_ever_ac_sol	.0398687	.01711	2.33	0.020	.0063338	.0734037
c_3charge	.0161555	.0127885	1.26	0.206	-.0089095	.0412205
c_p_medlim	.0013244	.0183622	0.07	0.943	-.0346648	.0373136
c_p_hsgrad	-.0092063	.0124995	-0.74	0.461	-.0337049	.0152922
c_p_had_job	.0067537	.0137444	0.49	0.623	-.0201848	.0336922
c_p_prob_drugalc	.0292767	.029622	0.99	0.323	-.0287814	.0873347
c_p_prob_mh	.0112291	.0142995	0.79	0.432	-.0167973	.0392555
c_p_usvet	-.0058098	.0262986	-0.22	0.825	-.0573541	.0457346
c_p_iq	.0000436	.0003905	0.11	0.911	-.0007218	.000809
c_18under_1arr	-.0041787	.014421	-0.29	0.772	-.0324434	.024086
c_apv	.0214736	.0245828	0.87	0.382	-.0267079	.069655
cp_age	-.0049372	.001459	-3.38	0.001	-.0077968	-.0020776
cp_black	-.0478443	.0311987	-1.53	0.125	-.1089926	.013304
cp_married	.0211809	.0443584	0.48	0.633	-.06576	.1081219
cp_islam	.0463427	.0412987	1.12	0.262	-.0346014	.1272867
cp_urban	-.04499	.0380424	-1.18	0.237	-.1195518	.0295718
cp_maxsent	-.0000294	.0001119	-0.26	0.792	-.0002488	.0001899
cp_pri_narr	.0059156	.0026026	2.27	0.023	.0008146	.0110166
cp_cust_gt3	.0334401	.0339656	0.98	0.325	-.0331312	.1000114
cp_misAB	.001043	.0348398	0.03	0.976	-.0672418	.0693278
cp_hadtc	-.0124065	.074617	-0.17	0.868	-.158653	.1338401
cp_hasPriorI	.0254003	.0467423	0.54	0.587	-.0662129	.1170135
cp_ever_ac_sol	.0412739	.0404123	1.02	0.307	-.0379328	.1204805
cp_3charge	.0175712	.0264073	0.67	0.506	-.0341862	.0693286
cp_p_medlim	-.0066554	.0360727	-0.18	0.854	-.0773565	.0640458
cp_p_hsgrad	.0056358	.0262106	0.22	0.830	-.0457361	.0570077
cp_p_had_job	-.0125788	.0262036	-0.48	0.631	-.0639369	.0387793
cp_p_prob_drugalc	-.018185	.0502381	-0.36	0.717	-.11665	.0802799
cp_p_prob_mh	-.020015	.0289788	-0.69	0.490	-.0768125	.0367825
cp_p_usvet	.0537729	.0561897	0.96	0.339	-.0563569	.1639026
cp_p_iq	-.0005251	.0008975	-0.59	0.559	-.0022842	.0012341
cp_18under_1arr	-.018829	.0327969	-0.57	0.566	-.0831097	.0454518
cp_apv	-.0287774	.0434242	-0.66	0.508	-.1138872	.0563324
stretches	-.0147949	.0131912	-1.12	0.262	-.0406492	.0110593
r_time2rel	.0000349	.0000457	0.76	0.445	-.0000547	.0001245
r_staytime	-.0001614	.0000496	-3.26	0.001	-.0002586	-.0000643
tier_tt_fa	-.0005816	.012994	-0.04	0.964	-.0260494	.0248862
k	.0588032	.0225574	2.61	0.009	.0145915	.1030148
_cons	1.085893	.1624543	6.68	0.000	.7674888	1.404298
Mills						
rho1-rho0	-.0706936	.0326862	-2.16	0.031	-.1347574	-.0066298
ATE						

```
       E(Y1-Y0)@X |    .049589   .0278762     1.78   0.075    -.0050474    .1042254
------------------------------------------------------------------------------------
(note: file mte_base_t120_posthas_post0.gph not found)
(file mte_base_t120_posthas_post0.gph saved)
(running parametric_polynomial on estimation sample)


Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                      Number of obs      =     10131
Treatment Model: Probit                          Replications       =        50
------------------------------------------------------------------------------------
                  |   Observed   Bootstrap                         Normal-based
        has_post0 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
Treated           |
       c_hasPriorI |   .0197721   .0191563     1.03   0.302    -.0177736    .0573178
       r_pri_narr |   .0247302   .0023382    10.58   0.000     .0201474     .029313
     rel_pri_narr |   .0005542   .0014756     0.38   0.707    -.0023379    .0034463
            r_age |  -.0103803   .0007942   -13.07   0.000    -.0119369   -.0088238
          r_black |   .0379552    .032569     1.17   0.244    -.0258788    .1017892
        r_married |  -.0054734   .0203552    -0.27   0.788    -.0453688     .034422
          r_islam |   .0630396   .0158207     3.98   0.000     .0320316    .0940476
          r_urban |  -.0183435   .0171573    -1.07   0.285    -.0519711    .0152841
        r_maxsent |  -.0002941    .000208    -1.41   0.157    -.0007017    .0001135
       r_cust_gt3 |   .0595702   .0129285     4.61   0.000     .0342309    .0849096
          r_misAB |   .0224455   .0156463     1.43   0.151    -.0082207    .0531117
          r_hadtc |   .0821848   .0305674     2.69   0.007     .0222739    .1420957
    r_ever_ac_sol |  -.0273724   .0163202    -1.68   0.094    -.0593593    .0046146
        r_3charge |   .0161112   .0125396     1.28   0.199     -.008466    .0406884
       r_p_medlim |  -.0195792   .0188875    -1.04   0.300     -.056598    .0174395
       r_p_hsgrad |  -.0223388   .0148395    -1.51   0.132    -.0514237    .0067461
      r_p_had_job |   .0278388   .0153562     1.81   0.070    -.0022587    .0579363
  r_p_prob_drugalc |    .074864   .0241361     3.10   0.002      .027558    .1221699
      r_p_prob_mh |   .0655683   .0139152     4.71   0.000     .0382951    .0928415
        r_p_usvet |  -.0458312   .0266592    -1.72   0.086    -.0980822    .0064198
           r_p_iq |    .000117   .0005201     0.23   0.822    -.0009023    .0011363
    r_18under_1arr |   .0202263   .0133312     1.52   0.129    -.0059025     .046355
            c_age |  -.0007463   .0009684    -0.77   0.441    -.0026443    .0011517
          c_black |  -.0004097   .0191957    -0.02   0.983    -.0380325    .0372132
        c_married |  -.0280046   .0179257    -1.56   0.118    -.0631383    .0071291
          c_islam |   .0039681   .0183436     0.22   0.829    -.0319846    .0399208
          c_urban |   .0040567   .0178035     0.23   0.820    -.0308376     .038951
        c_maxsent |   -.000083   .0000477    -1.74   0.082    -.0001764    .0000105
       c_cust_gt3 |  -.0049778   .0153225    -0.32   0.745    -.0350094    .0250539
          c_misAB |   .0150113   .0121271     1.24   0.216    -.0087574    .0387799
          c_hadtc |  -.0688434   .0322224    -2.14   0.033    -.1319981   -.0056888
    c_ever_ac_sol |   .0060523   .0158483     0.38   0.703    -.0250098    .0371144
        c_3charge |   .0045035    .013519     0.33   0.739    -.0219934    .0310003
       c_p_medlim |   .0031302   .0125119     0.25   0.802    -.0213926     .027653
       c_p_hsgrad |   .0033663   .0135997     0.25   0.804    -.0232885    .0300212
      c_p_had_job |   .0129231   .0111662     1.16   0.247    -.0089623    .0348085
  c_p_prob_drugalc |   .0049674   .0223059     0.22   0.824    -.0387514    .0486862
      c_p_prob_mh |   -.008147    .013617    -0.60   0.550    -.0348358    .0185417
        c_p_usvet |   .0085347   .0266834     0.32   0.749    -.0437638    .0608332
           c_p_iq |  -.0005863   .0005263    -1.11   0.265    -.0016178    .0004452
    c_18under_1arr |   .0074408   .0144571     0.51   0.607    -.0208946    .0357762
            c_apv |   .0010462   .0194875     0.05   0.957    -.0371487     .039241
           cp_age |  -.0025036   .0017708    -1.41   0.157    -.0059743    .0009671
         cp_black |   .0121477   .0365893     0.33   0.740    -.0595661    .0838614
       cp_married |    -.01767   .0369462    -0.48   0.632    -.0900832    .0547432
         cp_islam |   .0045475   .0431984     0.11   0.916    -.0801198    .0892149
         cp_urban |  -.0239555   .0329766    -0.73   0.468    -.0885886    .0406775
       cp_maxsent |   .0000621   .0001381     0.45   0.653    -.0002086    .0003328
      cp_pri_narr |   .0005835   .0029629     0.20   0.844    -.0052237    .0063907
      cp_cust_gt3 |   .0270523   .0316888     0.85   0.393    -.0350566    .0891612
         cp_misAB |  -.0556844   .0283627    -1.96   0.050    -.1112743   -.0000945
         cp_hadtc |  -.0840764   .0601711    -1.40   0.162    -.2020097    .0338568
      cp_hasPriorI |  -.0609041   .0452579    -1.35   0.178    -.1496079    .0277997
    cp_ever_ac_sol |   .0650047   .0364172     1.79   0.074    -.0063717    .1363811
       cp_3charge |   .0522011   .0267933     1.95   0.051    -.0003128     .104715
      cp_p_medlim |  -.0189416   .0342021    -0.55   0.580    -.0859765    .0480934
      cp_p_hsgrad |  -.0066349   .0323022    -0.21   0.837     -.069946    .0566762
     cp_p_had_job |  -.0288697   .0269508    -1.07   0.284    -.0816922    .0239528
 cp_p_prob_drugalc |  -.0295955   .0556243    -0.53   0.595    -.1386171    .0794262
     cp_p_prob_mh |   .0173432   .0297655     0.58   0.560    -.0409961    .0756825
       cp_p_usvet |  -.0447005   .0579513    -0.77   0.441    -.1582829     .068882
          cp_p_iq |   .0005122   .0010526     0.49   0.627    -.0015509    .0025753
   cp_18under_1arr |    .038444   .0306988     1.25   0.210    -.0217244    .0986125
           cp_apv |   .0860577   .0446645     1.93   0.054    -.0014831    .1735985
        stretches |  -.0023641   .0047538    -0.50   0.619    -.0116813    .0069531
       r_time2rel |  -4.85e-06   .0000253    -0.19   0.848    -.0000544    .0000447
       r_staytime |  -.0000268   .0000227    -1.18   0.238    -.0000713    .0000177
       tier_tt_fa |   .0291265   .0138661     2.10   0.036     .0019493    .0563036
                k |  -.0192882   .0222433    -0.87   0.386    -.0628843    .0243078
            _cons |   .8347609   .1631274     5.12   0.000     .5150371    1.154485
------------------+-----------------------------------------------------------------
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Untreated        |
     c_hasPriorI |   .0113426   .0181058     0.63   0.531    -.0241441    .0468292
      r_pri_narr |   .0217393   .0018897    11.50   0.000     .0180355    .0254431
    rel_pri_narr |   .0014826   .0009866     1.50   0.133    -.0004512    .0034163
           r_age |  -.0107542   .0008134   -13.22   0.000    -.0123485   -.0091599
         r_black |   .0445805   .0177195     2.52   0.012     .0098509    .0793101
       r_married |  -.0455246   .0159413    -2.86   0.004    -.0767691   -.0142802
         r_islam |   .0668409   .0180197     3.71   0.000      .031523    .1021588
         r_urban |  -.0059986   .0116788    -0.51   0.608    -.0288887    .0168915
       r_maxsent |  -.0002023   .0002808    -0.72   0.471    -.0007526     .000348
      r_cust_gt3 |   .0073767   .0176303     0.42   0.676    -.0271781    .0419316
         r_misAB |   .0499372   .0173869     2.87   0.004     .0158595    .0840148
         r_hadtc |   .0074447   .0507299     0.15   0.883    -.0919839    .1068734
    r_ever_ac_sol |   .0362879   .0238467     1.52   0.128    -.0104508    .0830267
       r_3charge |   .0183699   .0104509     1.76   0.079    -.0021135    .0388533
      r_p_medlim |  -.0026012   .0165239    -0.16   0.875    -.0349874     .029785
      r_p_hsgrad |  -.0363005    .012697    -2.86   0.004     -.061186   -.0114149
     r_p_had_job |   .0083503   .0157742     0.53   0.597    -.0225666    .0392672
 r_p_prob_drugalc |   .0702238   .0215042     3.27   0.001     .0280763    .1123713
     r_p_prob_mh |   .0806649   .0117066     6.89   0.000     .0577204    .1036094
       r_p_usvet |   .0082836   .0315405     0.26   0.793    -.0535346    .0701018
          r_p_iq |   .0001896   .0004771     0.40   0.691    -.0007455    .0011248
  r_18under_1arr |   .0292449   .0148591     1.97   0.049     .0001216    .0583683
           c_age |  -.0015329   .0008449    -1.81   0.070    -.0031888     .000123
         c_black |    .005883   .0144737     0.41   0.684    -.0224849    .0342509
       c_married |   .0110465    .015265     0.72   0.469    -.0188724    .0409653
         c_islam |  -.0139548   .0188518    -0.74   0.459    -.0509037    .0229941
         c_urban |  -.0140189   .0153498    -0.91   0.361     -.044104    .0160663
       c_maxsent |  -.0000378   .0000478    -0.79   0.429    -.0001315    .0000559
      c_cust_gt3 |   .0041774   .0147865     0.28   0.778    -.0248038    .0331585
         c_misAB |  -.0088394   .0128135    -0.69   0.490    -.0339534    .0162745
         c_hadtc |   .0276134   .0336532     0.82   0.412    -.0383458    .0935725
    c_ever_ac_sol |   .0373025   .0150086     2.49   0.013     .0078863    .0667188
       c_3charge |   .0161173   .0114457     1.41   0.159    -.0063158    .0385505
      c_p_medlim |  -.0016163   .0163297    -0.10   0.921    -.0336218    .0303892
      c_p_hsgrad |  -.0050154   .0106617    -0.47   0.638    -.0259118    .0158811
     c_p_had_job |   .0008905   .0140502     0.06   0.949    -.0266474    .0284284
 c_p_prob_drugalc |   .0299444   .0256051     1.17   0.242    -.0202407    .0801294
     c_p_prob_mh |   .0064308   .0130221     0.49   0.621    -.0190921    .0319537
       c_p_usvet |  -.0007046     .02922    -0.02   0.981    -.0579748    .0565655
          c_p_iq |   -.000128   .0004193    -0.31   0.760    -.0009499    .0006938
  c_18under_1arr |   .0043953   .0142605     0.31   0.758    -.0235548    .0323453
           c_apv |   .0134572   .0233852     0.58   0.565    -.0323769    .0592913
          cp_age |  -.0045538    .001391    -3.27   0.001    -.0072801   -.0018274
        cp_black |  -.0288782   .0275513    -1.05   0.295    -.0828778    .0251214
      cp_married |  -.0048587   .0427632    -0.11   0.910    -.0886731    .0789556
        cp_islam |   .0364485   .0375146     0.97   0.331    -.0370788    .1099759
        cp_urban |  -.0355324   .0271677    -1.31   0.191    -.0887802    .0177153
      cp_maxsent |  -2.05e-06   .0000982    -0.02   0.983    -.0001945    .0001904
     cp_pri_narr |   .0045614   .0024717     1.85   0.065    -.0002831    .0094059
     cp_cust_gt3 |   .0527475   .0257603     2.05   0.041     .0022584    .1032367
        cp_misAB |   .0150165   .0273912     0.55   0.584    -.0386693    .0687023
        cp_hadtc |  -.0075125    .082215    -0.09   0.927    -.1686509    .1536259
     cp_hasPriorI |   .0381792   .0418933     0.91   0.362    -.0439302    .1202885
   cp_ever_ac_sol |   .0161398   .0367901     0.44   0.661    -.0559674    .0882471
      cp_3charge |   .0075951    .026504     0.29   0.774    -.0443519     .059542
     cp_p_medlim |  -.0108772   .0287055    -0.38   0.705    -.0671389    .0453845
     cp_p_hsgrad |   .0062246   .0281449     0.22   0.825    -.0489384    .0613875
    cp_p_had_job |   .0143696   .0274029     0.52   0.600    -.0393391    .0680783
cp_p_prob_drugalc |  -.0258225   .0357487    -0.72   0.470    -.0958887    .0442437
    cp_p_prob_mh |  -.0237511   .0253485    -0.94   0.349    -.0734333    .0259311
      cp_p_usvet |    .022985   .0531394     0.43   0.665    -.0811663    .1271363
         cp_p_iq |  -.0005397   .0008617    -0.63   0.531    -.0022285    .0011492
  cp_18under_1arr |  -.0219095    .023556    -0.93   0.352    -.0680784    .0242595
          cp_apv |  -.0241348   .0467696    -0.52   0.606    -.1158015    .0675319
       stretches |  -.0164875   .0090765    -1.82   0.069    -.0342772    .0013022
      r_time2rel |   .0000164   .0000375     0.44   0.663    -.0000571    .0000899
      r_staytime |  -.0001451   .0000403    -3.60   0.000     -.000224   -.0000662
      tier_tt_fa |   .0016745    .012601     0.13   0.894     -.023023     .026372
               k |   .0518221   .0234131     2.21   0.027     .0059332     .097711
           _cons |   1.063632   .1197695     8.88   0.000     .8288878    1.298376
-----------------+----------------------------------------------------------------
Mills            |
       rho1-rho0 |  -.0711104   .0343873    -2.07   0.039    -.1385083   -.0037124
-----------------+----------------------------------------------------------------
ATE              |
      E(Y1-Y0)@X |   .0220948   .0223642     0.99   0.323    -.0217383    .0659278
----------------------------------------------------------------------------------
(note: file mte_base_t150_posthas_post0.gph not found)
(file mte_base_t150_posthas_post0.gph saved)
(running parametric_polynomial on estimation sample)


Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                     Number of obs      =     10131
Treatment Model: Probit                         Replications       =        50
```

has_post0	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
Treated						
c_hasPriorI	.0108157	.0216769	0.50	0.618	-.0316703	.0533018
r_pri_narr	.0247764	.002039	12.15	0.000	.02078	.0287728
rel_pri_narr	.0006924	.0013606	0.51	0.611	-.0019743	.003359
r_age	-.010586	.0011889	-8.90	0.000	-.0129163	-.0082558
r_black	.0360348	.0361524	1.00	0.319	-.0348226	.1068922
r_married	-.019848	.0227702	-0.87	0.383	-.0644766	.0247807
r_islam	.0606079	.0190742	3.18	0.001	.0232232	.0979926
r_urban	-.0173727	.0173367	-1.00	0.316	-.0513519	.0166066
r_maxsent	-.0004315	.000204	-2.11	0.034	-.0008314	-.0000316
r_cust_gt3	.071822	.0134744	5.33	0.000	.0454127	.0982314
r_misAB	.022952	.0150604	1.52	0.128	-.0065659	.0524699
r_hadtc	.0799068	.0298309	2.68	0.007	.0214394	.1383743
r_ever_ac_sol	-.0105353	.0220879	-0.48	0.633	-.0538268	.0327562
r_3charge	.0294607	.0111979	2.63	0.009	.0075132	.0514082
r_p_medlim	-.0108748	.0183744	-0.59	0.554	-.046888	.0251384
r_p_hsgrad	-.0292302	.0129631	-2.25	0.024	-.0546374	-.003823
r_p_had_job	.0333395	.0115972	2.87	0.004	.0106094	.0560696
r_p_prob_drugalc	.0563299	.0213527	2.64	0.008	.0144794	.0981804
r_p_prob_mh	.0619451	.0155133	3.99	0.000	.0315396	.0923505
r_p_usvet	-.0308302	.039049	-0.79	0.430	-.107365	.0457045
r_p_iq	-.0001002	.0005633	-0.18	0.859	-.0012043	.0010038
r_18under_1arr	.0241809	.0191607	1.26	0.207	-.0133734	.0617353
c_age	-.0012514	.0009725	-1.29	0.198	-.0031573	.0006546
c_black	-.0057967	.0234365	-0.25	0.805	-.0517313	.040138
c_married	-.0301195	.0180684	-1.67	0.096	-.065533	.0052939
c_islam	-.0074523	.0218408	-0.34	0.733	-.0502596	.035355
c_urban	.0212824	.0213361	1.00	0.319	-.0205356	.0631004
c_maxsent	-.0000448	.0000437	-1.03	0.305	-.0001304	.0000408
c_cust_gt3	-.0024862	.0195888	-0.13	0.899	-.0408795	.0359072
c_misAB	.0114367	.0160969	0.71	0.477	-.0201127	.042986
c_hadtc	-.0654552	.0252612	-2.59	0.010	-.1149663	-.0159442
c_ever_ac_sol	-.0021939	.0161508	-0.14	0.892	-.0338489	.029461
c_3charge	.0086205	.0141826	0.61	0.543	-.0191768	.0364179
c_p_medlim	-.0033722	.0169537	-0.20	0.842	-.0366008	.0298564
c_p_hsgrad	-.0007488	.014013	-0.05	0.957	-.0282137	.0267161
c_p_had_job	.0119441	.0144765	0.83	0.409	-.0164294	.0403175
c_p_prob_drugalc	.0109092	.0253548	0.43	0.667	-.0387853	.0606037
c_p_prob_mh	-.0014587	.0148294	-0.10	0.922	-.0305237	.0276063
c_p_usvet	.0067105	.0301108	0.22	0.824	-.0523055	.0657266
c_p_iq	-.0004492	.0005696	-0.79	0.430	-.0015655	.0006672
c_18under_1arr	-.000579	.01651	-0.04	0.972	-.0329379	.03178
c_apv	.0103799	.0269367	0.39	0.700	-.0424151	.0631749
cp_age	-.0026818	.0021984	-1.22	0.223	-.0069906	.001627
cp_black	.0141047	.0437301	0.32	0.747	-.0716046	.0998141
cp_married	-.0435488	.048239	-0.90	0.367	-.1380956	.050998
cp_islam	.0214172	.0376728	0.57	0.570	-.0524202	.0952546
cp_urban	-.0281262	.0357388	-0.79	0.431	-.0981729	.0419206
cp_maxsent	.0001765	.000113	1.56	0.118	-.0000449	.0003979
cp_pri_narr	.000702	.0036801	0.19	0.849	-.0065108	.0079148
cp_cust_gt3	.0270049	.027104	1.00	0.319	-.026118	.0801278
cp_misAB	-.049903	.0324757	-1.54	0.124	-.1135541	.0137482
cp_hadtc	-.081423	.065791	-1.24	0.216	-.2103709	.0475249
cp_hasPriorI	-.0425534	.0484137	-0.88	0.379	-.1374424	.0523357
cp_ever_ac_sol	.0369627	.0435852	0.85	0.396	-.0484627	.1223881
cp_3charge	.0435059	.0323818	1.34	0.179	-.0199613	.1069732
cp_p_medlim	-.0251009	.0386854	-0.65	0.516	-.1009228	.050721
cp_p_hsgrad	.0074501	.033595	0.22	0.824	-.0583949	.0732952
cp_p_had_job	-.0144203	.0378801	-0.38	0.703	-.0886639	.0598233
cp_p_prob_drugalc	-.0415575	.0627245	-0.66	0.508	-.1644953	.0813803
cp_p_prob_mh	.0253484	.0337422	0.75	0.453	-.0407851	.0914819
cp_p_usvet	.0223245	.0715762	0.31	0.755	-.1179623	.1626114
cp_p_iq	-.0002897	.0011242	-0.26	0.797	-.0024931	.0019137
cp_18under_1arr	.0385666	.0421438	0.92	0.360	-.0440337	.1211669
cp_apv	.0636163	.0626196	1.02	0.310	-.0591159	.1863485
stretches	-.0047941	.0054214	-0.88	0.377	-.01542	.0058317
r_time2rel	-7.02e-06	.0000273	-0.26	0.797	-.0000606	.0000466
r_staytime	-.0000182	.0000321	-0.57	0.571	-.000081	.0000447
tier_tt_fa	.0358282	.0150902	2.37	0.018	.006252	.0654043
k	-.0204386	.0280529	-0.73	0.466	-.0754212	.034544
_cons	.9163652	.1814131	5.05	0.000	.5608021	1.271928
Untreated						
c_hasPriorI	.0196808	.0177089	1.11	0.266	-.015028	.0543896
r_pri_narr	.022381	.0016595	13.49	0.000	.0191284	.0256336
rel_pri_narr	.0013911	.0009356	1.49	0.137	-.0004426	.0032249
r_age	-.0105712	.0007958	-13.28	0.000	-.012131	-.0090114
r_black	.0460923	.0157392	2.93	0.003	.015244	.0769406
r_married	-.0287232	.0161251	-1.78	0.075	-.0603278	.0028815
r_islam	.0685354	.0158357	4.33	0.000	.037498	.0995728
r_urban	-.0103035	.0156159	-0.66	0.509	-.04091	.0203031
r_maxsent	-.0000585	.0002219	-0.26	0.792	-.0004935	.0003764
r_cust_gt3	.0099027	.0143866	0.69	0.491	-.0182945	.0380998
r_misAB	.0399674	.0118399	3.38	0.001	.0167617	.0631731
r_hadtc	.0226415	.0376164	0.60	0.547	-.0510853	.0963683

```
   r_ever_ac_sol |   .0119195    .025889     0.46   0.645    -.0388219     .062661
       r_3charge |   .0079274   .0101938     0.78   0.437    -.0120521     .027907
      r_p_medlim |  -.0105481   .0145145    -0.73   0.467    -.0389959    .0178998
      r_p_hsgrad |  -.0297967   .0133626    -2.23   0.026    -.0559869   -.0036066
     r_p_had_job |   .0101188   .0134161     0.75   0.451    -.0161763    .0364138
 r_p_prob_drugalc |  .0853939   .0224952     3.80   0.000     .0413041    .1294836
     r_p_prob_mh |   .0819671   .0113024     7.25   0.000     .0598148    .1041195
       r_p_usvet |  -.0096983   .0255776    -0.38   0.705    -.0598294    .0404328
          r_p_iq |   .0002963   .0004244     0.70   0.485    -.0005356    .0011282
  r_18under_1arr |   .0268935   .0127653     2.11   0.035     .0018739    .0519132
           c_age |  -.0011728    .000964    -1.22   0.224    -.0030623    .0007166
         c_black |   .0073072   .0168386     0.43   0.664    -.0256958    .0403101
       c_married |   .0067554   .0167777     0.40   0.687    -.0261283     .039639
         c_islam |  -.0028416   .0186002    -0.15   0.879    -.0392974    .0336142
         c_urban |  -.0218409   .0127103    -1.72   0.086    -.0467527    .0030708
       c_maxsent |  -.0000766   .0000373    -2.05   0.040    -.0001498   -3.51e-06
      c_cust_gt3 |   .0035786   .0172276     0.21   0.835    -.0301868    .0373441
         c_misAB |  -.0021286   .0145156    -0.15   0.883    -.0305787    .0263215
         c_hadtc |   .0015505   .0258181     0.06   0.952     -.049052     .052153
   c_ever_ac_sol |   .0390075   .0165269     2.36   0.018     .0066153    .0713996
       c_3charge |   .0112577   .0129992     0.87   0.386    -.0142202    .0367355
      c_p_medlim |   .0044459   .0149019     0.30   0.765    -.0247613    .0336531
      c_p_hsgrad |   .0009632   .0109864     0.09   0.930    -.0205698    .0224961
     c_p_had_job |   .0024786   .0119664     0.21   0.836    -.0209751    .0259324
 c_p_prob_drugalc |  .0224507   .0212751     1.06   0.291    -.0192478    .0641492
     c_p_prob_mh |  -.0014173   .0096555    -0.15   0.883    -.0203418    .0175072
       c_p_usvet |   .0003401   .0231345     0.01   0.988    -.0450027    .0456829
          c_p_iq |  -.0003073   .0004208    -0.73   0.465     -.001132    .0005175
  c_18under_1arr |   .0104988   .0124993     0.84   0.401    -.0139994     .034997
           c_apv |    .000807   .0211642     0.04   0.970     -.040674     .042288
          cp_age |  -.0042752   .0012948    -3.30   0.001     -.006813   -.0017374
        cp_black |   -.025161   .0266248    -0.95   0.345    -.0773447    .0270226
      cp_married |   .0010526   .0355489     0.03   0.976    -.0686219    .0707271
        cp_islam |   .0214639   .0314284     0.68   0.495    -.0401346    .0830625
        cp_urban |  -.0331903   .0247705    -1.34   0.180    -.0817395    .0153589
      cp_maxsent |  -.0000506   .0000799    -0.63   0.526    -.0002072    .0001059
     cp_pri_narr |    .004105    .002482     1.65   0.098    -.0007596    .0089697
     cp_cust_gt3 |   .0475392   .0278456     1.71   0.088    -.0070371    .1021156
        cp_misAB |  -.0036992   .0298389    -0.12   0.901    -.0621824     .054784
        cp_hadtc |  -.0102188   .0714982    -0.14   0.886    -.1503526     .129915
     cp_hasPriorI |  .0163448   .0369013     0.44   0.658    -.0559804      .08867
   cp_ever_ac_sol |  .0410025   .0376289     1.09   0.276    -.0327488    .1147537
      cp_3charge |   .0179831      .0234     0.77   0.442      -.02788    .0638462
     cp_p_medlim |  -.0072755   .0317389    -0.23   0.819    -.0694826    .0549315
     cp_p_hsgrad |    -.00213   .0261062    -0.08   0.935    -.0532973    .0490374
    cp_p_had_job |   .0044091      .0231     0.19   0.849     -.040866    .0496842
 cp_p_prob_drugalc | -.0169437  .0388412    -0.44   0.663    -.0930711    .0591837
    cp_p_prob_mh |  -.0238095   .0245162    -0.97   0.331    -.0718604    .0242414
      cp_p_usvet |  -.0136945    .048127    -0.28   0.776    -.1080216    .0806326
         cp_p_iq |  -.0000588   .0007943    -0.07   0.941    -.0016155     .001498
  cp_18under_1arr |  -.0111029  .0299644    -0.37   0.711     -.069832    .0476263
          cp_apv |   .0038427   .0342001     0.11   0.911    -.0631884    .0708737
       stretches |   -.010316   .0094718    -1.09   0.276    -.0288804    .0082483
      r_time2rel |   .0000205   .0000274     0.75   0.455    -.0000332    .0000742
      r_staytime |  -.0001498   .0000343    -4.37   0.000    -.0002169   -.0000827
      tier_tt_fa |   .0003714   .0112196     0.03   0.974    -.0216185    .0223614
               k |   .0852891   .0245061     3.48   0.001      .037258    .1333201
           _cons |   .9831518    .120606     8.15   0.000     .7467684    1.219535
-----------------+----------------------------------------------------------------
Mills            |
       rho1-rho0 |  -.1057277   .0370873    -2.85   0.004    -.1784175   -.0330378
-----------------+----------------------------------------------------------------
ATE              |
      E(Y1-Y0)@X |   .0116342   .0331378     0.35   0.726    -.0533148    .0765832
----------------------------------------------------------------------------------
(note: file mte_base_t180_posthas_post0.gph not found)
(file mte_base_t180_posthas_post0.gph saved)
(running parametric_polynomial on estimation sample)
```

Outcome Model #2: An example of margte Output for Rearrest.

```
Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                     Number of obs      =     10131
Treatment Model: Probit                         Replications       =        50
---------------------------------------------------------------------------------
                 |   Observed   Bootstrap                         Normal-based
      has_postA  |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+---------------------------------------------------------------
Treated          |
     c_hasPriorI |   .0400399    .0167251     2.39   0.017     .0072593    .0728205
      r_pri_narr |   .0188266     .002113     8.91   0.000     .0146851    .0229681
```

rel_pri_narr	.0011789	.0012844	0.92	0.359	-.0013385	.0036963
r_rsth	.0488856	.0131328	3.72	0.000	.0231458	.0746254
rel_rsth	-.0059561	.0080598	-0.74	0.460	-.0217531	.0098409
r_age	-.0075354	.0010447	-7.21	0.000	-.0095831	-.0054878
r_black	.0380513	.0257053	1.48	0.139	-.0123301	.0884327
r_married	-.0130539	.0152661	-0.86	0.393	-.0429748	.0168671
r_islam	.0596777	.0183198	3.26	0.001	.0237715	.095584
r_urban	.0286392	.0170432	1.68	0.093	-.0047648	.0620432
r_maxsent	-.0012248	.000224	-5.47	0.000	-.0016638	-.0007859
r_cust_gt3	.0451404	.01162	3.88	0.000	.0223657	.0679152
r_misAB	-.0181033	.0201893	-0.90	0.370	-.0576735	.0214669
r_hadtc	.0329205	.0299923	1.10	0.272	-.0258632	.0917043
r_ever_ac_sol	-.0008435	.0140028	-0.06	0.952	-.0282886	.0266015
r_3charge	.0251724	.0130111	1.93	0.053	-.0003288	.0506736
r_p_medlim	-.011244	.0132779	-0.85	0.397	-.0372682	.0147801
r_p_hsgrad	-.0712275	.0176825	-4.03	0.000	-.1058845	-.0365706
r_p_had_job	.070457	.0112373	6.27	0.000	.0484322	.0924818
r_p_prob_drugalc	.0061062	.0250834	0.24	0.808	-.0430564	.0552687
r_p_prob_mh	.0223287	.0162	1.38	0.168	-.0094227	.0540801
r_p_usvet	-.0155208	.0259291	-0.60	0.549	-.0663409	.0352994
r_p_iq	.0002172	.0004855	0.45	0.655	-.0007345	.0011688
r_18under_1arr	-.0227561	.0192407	-1.18	0.237	-.0604671	.0149549
c_age	-.0016257	.0009497	-1.71	0.087	-.0034871	.0002358
c_black	.0058662	.0200607	0.29	0.770	-.0334521	.0451845
c_married	-.0158674	.0141582	-1.12	0.262	-.043617	.0118821
c_islam	.0102872	.0180225	0.57	0.568	-.0250361	.0456106
c_urban	.0021541	.0153866	0.14	0.889	-.0280031	.0323113
c_maxsent	-.0001003	.000037	-2.71	0.007	-.0001728	-.0000277
c_cust_gt3	-.0165531	.0138883	-1.19	0.233	-.0437737	.0106674
c_misAB	.0129754	.0148504	0.87	0.382	-.0161308	.0420817
c_hadtc	-.0381337	.0255305	-1.49	0.135	-.0881725	.0119051
c_ever_ac_sol	.0076457	.015398	0.50	0.620	-.0225338	.0378252
c_3charge	-.00669	.0132386	-0.51	0.613	-.0326371	.0192571
c_p_medlim	.0094511	.0148872	0.63	0.526	-.0197272	.0386294
c_p_hsgrad	-.0056242	.0142567	-0.39	0.693	-.0335668	.0223184
c_p_had_job	.0184381	.0115373	1.60	0.110	-.0041746	.0410508
c_p_prob_drugalc	-.0127345	.0231609	-0.55	0.582	-.0581291	.0326602
c_p_prob_mh	-.0191035	.0128958	-1.48	0.139	-.0443787	.0061717
c_p_usvet	-.0060468	.0291397	-0.21	0.836	-.0631596	.0510659
c_p_iq	-.0001442	.0003178	-0.45	0.650	-.0007671	.0004788
c_18under_1arr	.0228437	.0176101	1.30	0.195	-.0116713	.0573588
c_apv	.0090545	.0221667	0.41	0.683	-.0343915	.0525005
cp_age	-.0027018	.0020853	-1.30	0.195	-.0067889	.0013854
cp_black	.024351	.031521	0.77	0.440	-.037429	.086131
cp_married	-.0416081	.0411238	-1.01	0.312	-.1222093	.0389931
cp_islam	.0440427	.0329599	1.34	0.181	-.0205575	.108643
cp_urban	-.0412991	.0333216	-1.24	0.215	-.1066082	.0240099
cp_maxsent	.0001481	.0000784	1.89	0.059	-5.48e-06	.0003018
cp_pri_narr	.0015291	.0035947	0.43	0.671	-.0055164	.0085747
cp_cust_gt3	.0001219	.0258164	0.00	0.996	-.0504773	.0507212
cp_misAB	-.0075061	.0395972	-0.19	0.850	-.0851151	.070103
cp_hadtc	-.022441	.057505	-0.39	0.696	-.1351487	.0902667
cp_hasPriorI	-.0514832	.0440713	-1.17	0.243	-.1378613	.034895
cp_ever_ac_sol	.060427	.0316739	1.91	0.056	-.0016528	.1225068
cp_3charge	.0217124	.0248583	0.87	0.382	-.027009	.0704339
cp_rsth	-.0299539	.0227345	-1.32	0.188	-.0745127	.0146049
cp_p_medlim	-.0129214	.0357182	-0.36	0.718	-.0829278	.0570849
cp_p_hsgrad	.0054602	.032959	0.17	0.868	-.0591383	.0700587
cp_p_had_job	-.0204683	.0268545	-0.76	0.446	-.0731022	.0321656
cp_p_prob_drugalc	.0068152	.051547	0.13	0.895	-.0942151	.1078455
cp_p_prob_mh	.0412048	.0268398	1.54	0.125	-.0114002	.0938098
cp_p_usvet	-.0310338	.0494709	-0.63	0.530	-.1279949	.0659273
cp_p_iq	-.0001542	.0009359	-0.16	0.869	-.0019885	.0016801
cp_18under_1arr	.0831892	.0423753	1.96	0.050	.0001351	.1662433
cp_apv	.1106539	.0423608	2.61	0.009	.0276283	.1936796
stretches	.0021766	.0046157	0.47	0.637	-.0068701	.0112232
r_time2rel	.0000263	.0000205	1.28	0.199	-.0000138	.0000664
r_staytime	-.0000179	.0000251	-0.71	0.476	-.000067	.0000313
tier_tt_fa	.0348688	.0119196	2.93	0.003	.0115067	.0582308
k	-.0424946	.0249288	-1.70	0.088	-.0913541	.006365
_cons	.703168	.1469881	4.78	0.000	.4150767	.9912594
Untreated						
c_hasPriorI	.0066657	.0184975	0.36	0.719	-.0295887	.04292
r_pri_narr	.0130008	.002525	5.15	0.000	.0080519	.0179496
rel_pri_narr	.0007007	.001863	0.38	0.707	-.0029507	.0043521
r_rsth	.0879721	.0152637	5.76	0.000	.0580558	.1178884
rel_rsth	-.0038152	.0125222	-0.30	0.761	-.0283582	.0207278
r_age	-.005544	.0009891	-5.61	0.000	-.0074825	-.0036054
r_black	.0641104	.0191034	3.36	0.001	.0266683	.1015524
r_married	-.039878	.0141823	-2.81	0.005	-.0676749	-.0120812
r_islam	.0617002	.0193468	3.19	0.001	.0237812	.0996192
r_urban	.0351453	.0173799	2.02	0.043	.0010814	.0692092
r_maxsent	-.001702	.0003207	-5.31	0.000	-.0023305	-.0010735
r_cust_gt3	.0053009	.0217177	0.24	0.807	-.0372651	.0478669
r_misAB	-.0480064	.0295923	-1.62	0.105	-.1060062	.0099935
r_hadtc	-.0400989	.0551198	-0.73	0.467	-.1481317	.0679339
r_ever_ac_sol	.0209035	.0302681	0.69	0.490	-.0384209	.0802279
r_3charge	.0101194	.0148793	0.68	0.496	-.0190435	.0392823

```
        r_p_medlim |  -.0014679   .0200208    -0.07   0.942     -.040708    .0377722
        r_p_hsgrad |  -.1222971   .0213131    -5.74   0.000     -.16407    -.0805242
       r_p_had_job |   .0711259    .015135     4.70   0.000     .0414618    .1007899
   r_p_prob_drugalc |  -.0296923    .024442    -1.21   0.224    -.0775977    .0182132
       r_p_prob_mh |   .0558105   .0143361     3.89   0.000     .0277123    .0839086
         r_p_usvet |   -.029062   .0273181    -1.06   0.287    -.0826044    .0244805
            r_p_iq |   .0001782   .0005341     0.33   0.739    -.0008686    .0012251
     r_18under_1arr |  -.0569841   .0243568    -2.34   0.019    -.1047225   -.0092458
             c_age |  -.0011978    .001122    -1.07   0.286    -.0033968    .0010013
           c_black |  -.0144847   .0194156    -0.75   0.456    -.0525385    .0235692
         c_married |   .0074342   .0201067     0.37   0.712    -.0319742    .0468426
           c_islam |  -.0089664   .0187548    -0.48   0.633    -.0457252    .0277923
           c_urban |  -.0164796   .0162783    -1.01   0.311    -.0483844    .0154253
         c_maxsent |  -.0000664   .0000442    -1.50   0.133     -.000153    .0000203
         c_cust_gt3 |   .0248231   .0189727     1.31   0.191    -.0123627    .0620089
           c_misAB |   -.005036   .0220416    -0.23   0.819    -.0482368    .0381648
           c_hadtc |   .0650106   .0306827     2.12   0.034     .0048737    .1251476
      c_ever_ac_sol |   .0061112   .0207884     0.29   0.769    -.0346332    .0468556
         c_3charge |   .0062643   .0116233     0.54   0.590     -.016517    .0290455
         c_p_medlim |  -.0072966    .014364    -0.51   0.611    -.0354494    .0208563
         c_p_hsgrad |   .0014066    .019476     0.07   0.942    -.0367657    .0395788
       c_p_had_job |   .0120584   .0112666     1.07   0.284    -.0100237    .0341404
   c_p_prob_drugalc |   .0462062   .0291188     1.59   0.113    -.0108656    .1032781
       c_p_prob_mh |   .0137673   .0133008     1.04   0.301    -.0123018    .0398365
         c_p_usvet |  -.0172207   .0315036    -0.55   0.585    -.0789666    .0445253
            c_p_iq |   -.000568   .0004658    -1.22   0.223     -.001481     .000345
     c_18under_1arr |   .0078227   .0178711     0.44   0.662     -.027204    .0428494
             c_apv |   .0255369   .0302742     0.84   0.399    -.0337995    .0848732
            cp_age |  -.0033261   .0021806    -1.53   0.127    -.0075999    .0009477
          cp_black |  -.0590957   .0344487    -1.72   0.086    -.1266139    .0084224
        cp_married |   .0721884   .0382301     1.89   0.059    -.0027412     .147118
          cp_islam |   .0834001   .0429928     1.94   0.052    -.0008642    .1676645
          cp_urban |  -.0132546   .0323847    -0.41   0.682    -.0767274    .0502183
        cp_maxsent |  -.0000525   .0000995    -0.53   0.598    -.0002474    .0001425
       cp_pri_narr |   .0019992    .003525     0.57   0.571    -.0049097     .008908
       cp_cust_gt3 |    .020162   .0330307     0.61   0.542     -.044577     .084901
          cp_misAB |  -.0335355   .0438997    -0.76   0.445    -.1195774    .0525063
          cp_hadtc |  -.0090752   .0719343    -0.13   0.900    -.1500639    .1319135
       cp_hasPriorI |     .04683   .0445215     1.05   0.293    -.0404306    .1340906
     cp_ever_ac_sol |    .029276    .037529     0.78   0.435    -.0442795    .1028315
        cp_3charge |  -.0141465   .0270505    -0.52   0.601    -.0671644    .0388715
           cp_rsth |   .0397237   .0233744     1.70   0.089    -.0060893    .0855367
       cp_p_medlim |  -.0198551   .0337222    -0.59   0.556    -.0859494    .0462392
       cp_p_hsgrad |  -.0522645   .0352329    -1.48   0.138    -.1213198    .0167908
      cp_p_had_job |  -.0191777   .0253153    -0.76   0.449    -.0687947    .0304393
  cp_p_prob_drugalc |  -.0471125   .0480469    -0.98   0.327    -.1412827    .0470577
      cp_p_prob_mh |  -.0128689   .0263183    -0.49   0.625    -.0644519     .038714
        cp_p_usvet |    .057688   .0504576     1.14   0.253    -.0412071    .1565831
           cp_p_iq |    -.00033    .000958    -0.34   0.731    -.0022076    .0015476
    cp_18under_1arr |  -.0799762   .0402527    -1.99   0.047     -.15887    -.0010824
            cp_apv |  -.1067122   .0489691    -2.18   0.029    -.2026898   -.0107345
         stretches |  -.0142943   .0125304    -1.14   0.254    -.0388535    .0102648
         r_time2rel |   .0000638   .0000464     1.37   0.169    -.0000272    .0001548
        r_staytime |  -.0000943   .0000484    -1.95   0.052    -.0001892    6.33e-07
        tier_tt_fa |   .0105585   .0135954     0.78   0.437     -.016088    .0372051
                 k |   .0379571    .017845     2.13   0.033     .0029815    .0729327
             _cons |   .5563183   .1747941     3.18   0.001      .213728    .8989085
-------------------+----------------------------------------------------------------
Mills              |
         rho1-rho0 |  -.0804516   .0293228    -2.74   0.006    -.1379234   -.0229799
-------------------+----------------------------------------------------------------
ATE                |
         E(Y1-Y0)@X |   .0190386   .0263585     0.72   0.470    -.0326231    .0707003
------------------------------------------------------------------------------------
(note: file mte_base_t120_has_postA.gph not found)
(file mte_base_t120_has_postA.gph saved)
(running parametric_polynomial on estimation sample)


Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                      Number of obs      =     10131
Treatment Model: Probit                          Replications       =        50
------------------------------------------------------------------------------------
                   |   Observed   Bootstrap                         Normal-based
         has_postA |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
Treated            |
       c_hasPriorI |   .0377682   .0224955     1.68   0.093    -.0063221    .0818585
        r_pri_narr |   .0187364   .0028617     6.55   0.000     .0131276    .0243452
       rel_pri_narr |   .0014709   .0013543     1.09   0.277    -.0011835    .0041254
            r_rsth |   .0492776   .0152942     3.22   0.001     .0193015    .0792537
          rel_rsth |  -.0124301   .0104291    -1.19   0.233    -.0328708    .0080106
             r_age |  -.0068288   .0010147    -6.73   0.000    -.0088177   -.0048399
           r_black |   .0375897    .028969     1.30   0.194    -.0191884    .0943678
         r_married |   .0071042   .0202839     0.35   0.726    -.0326516    .0468599
           r_islam |    .056257   .0178503     3.15   0.002     .0212711    .0912429
```

r_urban	.0296911	.0178826	1.66	0.097	-.0053582	.0647405
r_maxsent	-.001259	.0001924	-6.54	0.000	-.001636	-.0008819
r_cust_gt3	.0502732	.0189288	2.66	0.008	.0131735	.0873729
r_misAB	-.0207296	.0187902	-1.10	0.270	-.0575576	.0160985
r_hadtc	.039427	.0275502	1.43	0.152	-.0145705	.0934244
r_ever_ac_sol	-.0155058	.0182754	-0.85	0.396	-.051325	.0203134
r_3charge	.0266802	.0112016	2.38	0.017	.0047255	.0486349
r_p_medlim	-.0109953	.0175043	-0.63	0.530	-.0453032	.0233126
r_p_hsgrad	-.0741633	.0178275	-4.16	0.000	-.1091046	-.039222
r_p_had_job	.0685404	.0137024	5.00	0.000	.0416842	.0953966
r_p_prob_drugalc	.007719	.0258653	0.30	0.765	-.042976	.058414
r_p_prob_mh	.0221179	.0159032	1.39	0.164	-.0090518	.0532877
r_p_usvet	-.0388726	.0294711	-1.32	0.187	-.0966349	.0188898
r_p_iq	-.0000319	.000563	-0.06	0.955	-.0011353	.0010716
r_18under_1arr	-.0341396	.0214931	-1.59	0.112	-.0762652	.007986
c_age	-.0023487	.0010157	-2.31	0.021	-.0043395	-.0003579
c_black	-.0056958	.0193437	-0.29	0.768	-.0436086	.0322171
c_married	-.0299687	.0198632	-1.51	0.131	-.0688998	.0089624
c_islam	.0236229	.0151897	1.56	0.120	-.0061483	.0533941
c_urban	.0125471	.0171633	0.73	0.465	-.0210924	.0461866
c_maxsent	-.0001002	.0000454	-2.21	0.027	-.0001891	-.0000113
c_cust_gt3	-.0127726	.014373	-0.89	0.374	-.0409432	.015398
c_misAB	.0223072	.0194409	1.15	0.251	-.0157963	.0604106
c_hadtc	-.057535	.0276006	-2.08	0.037	-.1116312	-.0034388
c_ever_ac_sol	-.0036626	.0163803	-0.22	0.823	-.0357673	.0284421
c_3charge	-.0094213	.0122605	-0.77	0.442	-.0334515	.0146089
c_p_medlim	.0135127	.0163118	0.83	0.407	-.0184579	.0454833
c_p_hsgrad	-.0020459	.0173456	-0.12	0.906	-.0360428	.0319509
c_p_had_job	.0186841	.0122184	1.53	0.126	-.0052636	.0426318
c_p_prob_drugalc	-.014185	.0336524	-0.42	0.673	-.0801425	.0517724
c_p_prob_mh	-.0225059	.0134816	-1.67	0.095	-.0489295	.0039176
c_p_usvet	-.0083684	.036751	-0.23	0.820	-.080399	.0636622
c_p_iq	-.0001468	.0005398	-0.27	0.786	-.0012048	.0009112
c_18under_1arr	.0238616	.0192089	1.24	0.214	-.0137872	.0615104
c_apv	.0240509	.0251321	0.96	0.339	-.025207	.0733089
cp_age	-.0022445	.0024974	-0.90	0.369	-.0071394	.0026504
cp_black	.029752	.0446037	0.67	0.505	-.0576696	.1171737
cp_married	-.0158311	.0460002	-0.34	0.731	-.1059898	.0743277
cp_islam	.0351864	.0448736	0.78	0.433	-.0527642	.1231371
cp_urban	-.034502	.0316858	-1.09	0.276	-.096605	.0276009
cp_maxsent	.0001338	.0001083	1.24	0.217	-.0000785	.0003461
cp_pri_narr	.0017138	.0033459	0.51	0.608	-.004844	.0082716
cp_cust_gt3	-.0133389	.0317517	-0.42	0.674	-.075571	.0488933
cp_misAB	-.0274063	.0434858	-0.63	0.529	-.1126369	.0578244
cp_hadtc	-.0441584	.0657503	-0.67	0.502	-.1730266	.0847098
cp_hasPriorI	-.0560433	.0503308	-1.11	0.265	-.1546898	.0426033
cp_ever_ac_sol	.0696981	.0377563	1.85	0.065	-.004303	.1436992
cp_3charge	.0328083	.0285733	1.15	0.251	-.0231943	.088811
cp_rsth	-.0246192	.0226099	-1.09	0.276	-.0689338	.0196953
cp_p_medlim	-.0025219	.0311941	-0.08	0.936	-.0636613	.0586175
cp_p_hsgrad	-.0041781	.0364437	-0.11	0.909	-.0756064	.0672502
cp_p_had_job	-.049752	.0273278	-1.82	0.069	-.1033134	.0038095
cp_p_prob_drugalc	.0097101	.0622185	0.16	0.876	-.1122359	.1316562
cp_p_prob_mh	.0468768	.0267154	1.75	0.079	-.0054844	.099238
cp_p_usvet	.0029355	.0665522	0.04	0.965	-.1275044	.1333754
cp_p_iq	.0003334	.0011489	0.29	0.772	-.0019184	.0025853
cp_18under_1arr	.0996932	.0491012	2.03	0.042	.0034567	.1959298
cp_apv	.1023686	.052789	1.94	0.052	-.001096	.2058331
stretches	.0038431	.0051263	0.75	0.453	-.0062042	.0138905
r_time2rel	.0000238	.0000234	1.02	0.310	-.0000221	.0000697
r_staytime	-6.69e-07	.0000216	-0.03	0.975	-.0000431	.0000417
tier_tt_fa	.0379666	.0118782	3.20	0.001	.0146858	.0612474
k	-.0451633	.0232721	-1.94	0.052	-.0907758	.0004491
_cons	.6089833	.1772564	3.44	0.001	.261567	.9563995
Untreated						
c_hasPriorI	.0182874	.020136	0.91	0.364	-.0211784	.0577531
r_pri_narr	.0142907	.0024189	5.91	0.000	.0095498	.0190316
rel_pri_narr	.0006464	.0014841	0.44	0.663	-.0022623	.0035551
r_rsth	.0788854	.0143631	5.49	0.000	.0507343	.1070364
rel_rsth	.0008521	.0087638	0.10	0.923	-.0163247	.0180289
r_age	-.006538	.0011028	-5.93	0.000	-.0086994	-.0043766
r_black	.0651322	.0160739	4.05	0.000	.0336279	.0966366
r_married	-.05148	.0202174	-2.55	0.011	-.0911054	-.0118547
r_islam	.0635036	.0184295	3.45	0.001	.0273824	.0996247
r_urban	.03496	.0134293	2.60	0.009	.008639	.0612809
r_maxsent	-.0015056	.0003166	-4.76	0.000	-.002126	-.0008851
r_cust_gt3	.008414	.0183813	0.46	0.647	-.0276125	.0444406
r_misAB	-.0416154	.0228412	-1.82	0.068	-.0863834	.0031526
r_hadtc	-.0082441	.0500686	-0.16	0.869	-.1063768	.0898886
r_ever_ac_sol	.0359748	.0239708	1.50	0.133	-.0110071	.0829567
r_3charge	.0131731	.0161258	0.82	0.414	-.018433	.0447791
r_p_medlim	-.0060593	.0181516	-0.33	0.739	-.0416357	.0295171
r_p_hsgrad	-.110225	.01952	-5.65	0.000	-.1484835	-.0719666
r_p_had_job	.0714911	.0139212	5.14	0.000	.0442061	.0987762
r_p_prob_drugalc	-.0291086	.029363	-0.99	0.322	-.0866589	.0284418
r_p_prob_mh	.0512748	.0143141	3.58	0.000	.0232196	.0793299
r_p_usvet	-.0018442	.0270096	-0.07	0.946	-.0547821	.0510936
r_p_iq	.0004394	.0004056	1.08	0.279	-.0003556	.0012343

```
    r_18under_1arr |   -.040357   .0208241    -1.94   0.053    -.0811714    .0004574
             c_age |  -.0007898   .0010079    -0.78   0.433    -.0027653    .0011856
           c_black |  -.0021201   .0158665    -0.13   0.894    -.0332179    .0289776
         c_married |   .0189263   .0203093     0.93   0.351    -.0208792    .0587319
           c_islam |  -.0168687   .0166452    -1.01   0.311    -.0494928    .0157553
           c_urban |  -.0214737   .0151121    -1.42   0.155    -.0510929    .0081454
         c_maxsent |  -.0000646   .0000353    -1.83   0.067    -.0001338    4.59e-06
        c_cust_gt3 |   .0156272   .0147499     1.06   0.289     -.013282    .0445364
          c_misAB |  -.0082432   .0190753    -0.43   0.666    -.0456301    .0291438
           c_hadtc |   .0658986   .0285399     2.31   0.021     .0099614    .1218358
     c_ever_ac_sol |   .0220235   .0177632     1.24   0.215    -.0127918    .0568387
        c_3charge |   .0051804   .0121361     0.43   0.669    -.0186058    .0289667
        c_p_medlim |   -.006397    .018243    -0.35   0.726    -.0421527    .0293586
       c_p_hsgrad |  -.0060873   .0153466    -0.40   0.692    -.0361661    .0239914
      c_p_had_job |   .0113236   .0117862     0.96   0.337    -.0117768    .0344241
  c_p_prob_drugalc |   .0390363   .0300447     1.30   0.194    -.0198501    .0979228
      c_p_prob_mh |   .0101347   .0124544     0.81   0.416    -.0142754    .0345448
        c_p_usvet |  -.0084584   .0246589    -0.34   0.732    -.0567889    .0398721
           c_p_iq |  -.0004116   .0004549    -0.90   0.366    -.0013031      .00048
    c_18under_1arr |   .0093924   .0189212     0.50   0.620    -.0276925    .0464774
            c_apv |   .0043359   .0236303     0.18   0.854    -.0419787    .0506505
           cp_age |  -.0035852   .0017275    -2.08   0.038    -.0069711   -.0001993
         cp_black |  -.0502185   .0257332    -1.95   0.051    -.1006547    .0002177
       cp_married |     .04069   .0400029     1.02   0.309    -.0377141    .1190942
         cp_islam |   .0846701    .040655     2.08   0.037     .0049877    .1643524
         cp_urban |  -.0191006   .0308765    -0.62   0.536    -.0796174    .0414161
       cp_maxsent |   7.15e-07   .0000776     0.01   0.993    -.0001513    .0001527
      cp_pri_narr |   .0013968   .0028489     0.49   0.624    -.0041869    .0069804
      cp_cust_gt3 |   .0273669    .035713     0.77   0.443    -.0426292    .0973631
         cp_misAB |  -.0166676   .0411729    -0.40   0.686    -.0973649    .0640298
         cp_hadtc |    -.01169   .0680099    -0.17   0.864    -.1449871     .121607
     cp_hasPriorI |   .0355854   .0363951     0.98   0.328    -.0357478    .1069186
    cp_ever_ac_sol |   .0265007   .0373814     0.71   0.478    -.0467654    .0997669
       cp_3charge |  -.0234387   .0254897    -0.92   0.358    -.0733975    .0265201
          cp_rsth |   .0250435   .0186558     1.34   0.179    -.0115212    .0616082
      cp_p_medlim |  -.0267408   .0369303    -0.72   0.469    -.0991228    .0456411
      cp_p_hsgrad |  -.0354247   .0334896    -1.06   0.290    -.1010632    .0302138
     cp_p_had_job |   .0011407   .0253718     0.04   0.964    -.0485871    .0508686
 cp_p_prob_drugalc |  -.0396971   .0485665    -0.82   0.414    -.1348857    .0554915
     cp_p_prob_mh |  -.0093342   .0254206    -0.37   0.713    -.0591576    .0404892
       cp_p_usvet |    .023622   .0438566     0.54   0.590    -.0623354    .1095794
          cp_p_iq |  -.0004461   .0006408    -0.70   0.486    -.0017019    .0008098
   cp_18under_1arr |  -.0633458   .0384243    -1.65   0.099    -.1386562    .0119645
           cp_apv |  -.0629792   .0496652    -1.27   0.205    -.1603212    .0343629
        stretches |  -.0148058   .0123664    -1.20   0.231    -.0390436    .0094319
       r_time2rel |   .0000366   .0000449     0.82   0.415    -.0000514    .0001245
       r_staytime |  -.0000756   .0000465    -1.62   0.104    -.0001669    .0000156
       tier_tt_fa |   .0148698   .0083065     1.79   0.073    -.0014107    .0311503
                k |     .03238   .0232702     1.39   0.164    -.0132288    .0779887
            _cons |   .6202317   .1466619     4.23   0.000     .3327796    .9076837
------------------+----------------------------------------------------------------
Mills             |
         rho1-rho0 |  -.0775433   .0308707    -2.51   0.012    -.1380488   -.0170378
------------------+----------------------------------------------------------------
ATE               |
        E(Y1-Y0)@X |   -.012829   .0315857    -0.41   0.685    -.0747359    .0490779
-----------------------------------------------------------------------------------
(note: file mte_base_t150_has_postA.gph not found)
(file mte_base_t150_has_postA.gph saved)
(running parametric_polynomial on estimation sample)


Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                        Number of obs      =     10131
Treatment Model: Probit                            Replications       =        50
-----------------------------------------------------------------------------------
                  |   Observed   Bootstrap                         Normal-based
        has_postA |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+----------------------------------------------------------------
Treated           |
      c_hasPriorI |   .0329786   .0207818     1.59   0.113     -.007753    .0737103
       r_pri_narr |   .0182384   .0025306     7.21   0.000     .0132785    .0231983
     rel_pri_narr |   .0011282   .0014194     0.79   0.427    -.0016538    .0039101
           r_rsth |    .060606   .0151102     4.01   0.000     .0309905    .0902215
         rel_rsth |  -.0035661   .0105953    -0.34   0.736    -.0243325    .0172004
            r_age |  -.0071387   .0011336    -6.30   0.000    -.0093604   -.0049169
          r_black |   .0308282   .0357723     0.86   0.389    -.0392843    .1009407
        r_married |   .0007371   .0221374     0.03   0.973    -.0426513    .0441256
          r_islam |   .0545872   .0211412     2.58   0.010     .0131511    .0960232
          r_urban |   .0313237   .0199736     1.57   0.117    -.0078238    .0704712
        r_maxsent |  -.0013276   .0002111    -6.29   0.000    -.0017413   -.0009138
       r_cust_gt3 |    .056284   .0211094     2.67   0.008     .0149103    .0976576
          r_misAB |   -.016815   .0185584    -0.91   0.365    -.0531889    .0195588
          r_hadtc |   .0406022   .0347164     1.17   0.242    -.0274407    .1086451
     r_ever_ac_sol |  -.0004126   .0217193    -0.02   0.985    -.0429817    .0421565
        r_3charge |   .0454742     .01355     3.36   0.001     .0189166    .0720318
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r_p_medlim	.0053752	.0173565	0.31	0.757	-.0286429	.0393932
r_p_hsgrad	-.0805923	.0210204	-3.83	0.000	-.1217916	-.039393
r_p_had_job	.0728623	.0169419	4.30	0.000	.0396567	.1060678
r_p_prob_drugalc	-.0097174	.0329375	-0.30	0.768	-.0742738	.0548389
r_p_prob_mh	.0168908	.0157645	1.07	0.284	-.014007	.0477886
r_p_usvet	-.0264733	.0275554	-0.96	0.337	-.0804808	.0275342
r_p_iq	-.0000561	.0006192	-0.09	0.928	-.0012698	.0011576
r_18under_1arr	-.0329714	.0239559	-1.38	0.169	-.0799241	.0139812
c_age	-.002501	.0012606	-1.98	0.047	-.0049718	-.0000303
c_black	-.012753	.0235481	-0.54	0.588	-.0589063	.0334003
c_married	-.0343474	.0216643	-1.59	0.113	-.0768086	.0081137
c_islam	.0221952	.021875	1.01	0.310	-.0206791	.0650695
c_urban	.0246102	.0204819	1.20	0.230	-.0155337	.064754
c_maxsent	-.0000315	.0000407	-0.77	0.440	-.0001113	.0000484
c_cust_gt3	-.0126162	.0174221	-0.72	0.469	-.0467629	.0215306
c_misAB	.0074022	.0201013	0.37	0.713	-.0319957	.0468001
c_hadtc	-.0526421	.0312918	-1.68	0.093	-.1139729	.0086887
c_ever_ac_sol	-.0213947	.0204108	-1.05	0.295	-.0613991	.0186097
c_3charge	-.0024744	.0159199	-0.16	0.876	-.0336767	.028728
c_p_medlim	.011195	.0156466	0.72	0.474	-.0194719	.0418618
c_p_hsgrad	-.0065636	.020214	-0.32	0.745	-.0461824	.0330552
c_p_had_job	.0163628	.0170064	0.96	0.336	-.0169691	.0496948
c_p_prob_drugalc	-.0148078	.0267822	-0.55	0.580	-.0672999	.0376843
c_p_prob_mh	-.0101926	.0123239	-0.83	0.408	-.0343471	.0139618
c_p_usvet	-.0093634	.0285517	-0.33	0.743	-.0653236	.0465969
c_p_iq	-4.92e-06	.0006163	-0.01	0.994	-.0012128	.0012029
c_18under_1arr	-.0020006	.0211696	-0.09	0.925	-.0434922	.0394911
c_apv	.0070089	.028719	0.24	0.807	-.0492792	.0632971
cp_age	-.0030855	.0025376	-1.22	0.224	-.0080591	.0018881
cp_black	.0301023	.0403042	0.75	0.455	-.0488924	.109097
cp_married	-.0341274	.0483832	-0.71	0.481	-.1289567	.0607018
cp_islam	.056471	.0442067	1.28	0.201	-.0301726	.1431146
cp_urban	-.0340524	.0418979	-0.81	0.416	-.1161709	.048066
cp_maxsent	.000198	.0001211	1.63	0.102	-.0000395	.0004354
cp_pri_narr	.0057853	.0039476	1.47	0.143	-.001952	.0135225
cp_cust_gt3	-.0264047	.0396416	-0.67	0.505	-.1041009	.0512915
cp_misAB	.0091471	.0484928	0.19	0.850	-.0858972	.1041913
cp_hadtc	-.0579486	.0658138	-0.88	0.379	-.1869413	.071044
cp_hasPriorI	-.0610645	.0483357	-1.26	0.206	-.1558007	.0336717
cp_ever_ac_sol	.067	.0374402	1.79	0.074	-.0063815	.1403816
cp_3charge	.0281539	.0315693	0.89	0.372	-.0337207	.0900286
cp_rsth	-.0525018	.0227142	-2.31	0.021	-.0970208	-.0079829
cp_p_medlim	-.0180857	.0346025	-0.52	0.601	-.0859054	.049734
cp_p_hsgrad	.0250371	.0426833	0.59	0.557	-.0586207	.1086948
cp_p_had_job	-.0505169	.0332658	-1.52	0.129	-.1157166	.0146828
cp_p_prob_drugalc	.0118763	.0665756	0.18	0.858	-.1186095	.1423622
cp_p_prob_mh	.0479986	.0327317	1.47	0.143	-.0161542	.1121515
cp_p_usvet	.0568098	.0604416	0.94	0.347	-.0616534	.1752731
cp_p_iq	-.0000688	.0013074	-0.05	0.958	-.0026313	.0024937
cp_18under_1arr	.1442559	.0468001	3.08	0.002	.0525295	.2359823
cp_apv	.116216	.0639204	1.82	0.069	-.0090656	.2414976
stretches	.0018195	.0061571	0.30	0.768	-.0102482	.0138871
r_time2rel	.0000274	.0000222	1.23	0.217	-.0000161	.0000708
r_staytime	-1.86e-08	.0000256	-0.00	0.999	-.0000502	.0000501
tier_tt_fa	.0428389	.0123377	3.47	0.001	.0186574	.0670204
k	-.0333208	.0265755	-1.25	0.210	-.0854077	.0187662
_cons	.6874466	.208479	3.30	0.001	.2788352	1.096058
Untreated						
c_hasPriorI	.0271708	.0204236	1.33	0.183	-.0128587	.0672003
r_pri_narr	.0153922	.002557	6.02	0.000	.0103806	.0204038
rel_pri_narr	.0010337	.0014574	0.71	0.478	-.0018229	.0038902
r_rsth	.0677782	.0130785	5.18	0.000	.0421449	.0934115
rel_rsth	-.0068195	.0090264	-0.76	0.450	-.0245108	.0108718
r_age	-.0064421	.0008858	-7.27	0.000	-.0081781	-.004706
r_black	.0675514	.0192754	3.50	0.000	.0297723	.1053305
r_married	-.0358911	.0166581	-2.15	0.031	-.0685403	-.0032419
r_islam	.0625755	.0158596	3.95	0.000	.0314913	.0936597
r_urban	.0299392	.0137048	2.18	0.029	.0030783	.0568
r_maxsent	-.0014199	.0002582	-5.50	0.000	-.0019261	-.0009138
r_cust_gt3	.0150438	.0122631	1.23	0.220	-.0089915	.0390791
r_misAB	-.0467325	.0200116	-2.34	0.020	-.0859544	-.0075105
r_hadtc	-.014161	.0339916	-0.42	0.677	-.0807834	.0524614
r_ever_ac_sol	.01623	.0223956	0.72	0.469	-.0276647	.0601246
r_3charge	.0025872	.0102431	0.25	0.801	-.017489	.0226634
r_p_medlim	-.0179558	.0179814	-1.00	0.318	-.0531987	.0172871
r_p_hsgrad	-.1016212	.0161606	-6.29	0.000	-.1332955	-.069947
r_p_had_job	.0701901	.0128826	5.45	0.000	.0449407	.0954396
r_p_prob_drugalc	-.0102385	.025918	-0.40	0.693	-.0610368	.0405597
r_p_prob_mh	.0516283	.0110863	4.66	0.000	.0298995	.0733572
r_p_usvet	-.0147306	.0247545	-0.60	0.552	-.0632484	.0337873
r_p_iq	.0003448	.0004078	0.85	0.398	-.0004545	.001144
r_18under_1arr	-.0404492	.0205868	-1.96	0.049	-.0807987	-.0000998
c_age	-.0009593	.0010325	-0.93	0.353	-.0029829	.0010644
c_black	.0007571	.012679	0.06	0.952	-.0240933	.0256075
c_married	.0142135	.0159837	0.89	0.374	-.0171139	.045541
c_islam	-.0097394	.0142571	-0.68	0.495	-.0376829	.0182041
c_urban	-.0228364	.0133214	-1.71	0.086	-.0489459	.0032731
c_maxsent	-.0001217	.0000475	-2.56	0.010	-.0002148	-.0000286

```
     c_cust_gt3 |   .0133578   .0124284     1.07   0.282    -.0110015    .0377171
        c_misAB |   .0053677   .0182824     0.29   0.769    -.0304652    .0412006
        c_hadtc |   .0364177   .0263504     1.38   0.167    -.0152281    .0880635
  c_ever_ac_sol |   .0309127     .01632     1.89   0.058    -.0010738    .0628993
      c_3charge |  -.0016137   .0131629    -0.12   0.902    -.0274126    .0241851
      c_p_medlim |    .000802   .0132138     0.06   0.952    -.0250966    .0267006
      c_p_hsgrad |   .0005997   .0153747     0.04   0.969    -.0295342    .0307336
     c_p_had_job |   .0139026   .0118244     1.18   0.240    -.0092729     .037078
c_p_prob_drugalc |   .0324677   .0247869     1.31   0.190    -.0161137    .0810492
    c_p_prob_mh |  -.0029726    .012919    -0.23   0.818    -.0282935    .0223483
      c_p_usvet |  -.0099508   .0249296    -0.40   0.690     -.058812    .0389105
         c_p_iq |  -.0004894   .0004117    -1.19   0.235    -.0012962    .0003175
  c_18under_1arr |   .0283664   .0169829     1.67   0.095    -.0049195    .0616523
          c_apv |   .0141899    .019098     0.74   0.457    -.0232415    .0516213
         cp_age |  -.0030691   .0014623    -2.10   0.036    -.0059352   -.0002031
       cp_black |  -.0398956   .0351677    -1.13   0.257    -.1088231    .0290319
     cp_married |   .0385389   .0285967     1.35   0.178    -.0175096    .0945875
       cp_islam |    .062998   .0371914     1.69   0.090    -.0098958    .1358919
       cp_urban |  -.0212732   .0307889    -0.69   0.490    -.0816183    .0390718
     cp_maxsent |  -.0000238   .0000941    -0.25   0.801    -.0002081    .0001606
    cp_pri_narr |  -.0004305   .0025981    -0.17   0.868    -.0055228    .0046617
    cp_cust_gt3 |   .0250386   .0259798     0.96   0.335    -.0258809    .0759581
       cp_misAB |  -.0428452   .0371118    -1.15   0.248     -.115583    .0298926
       cp_hadtc |    .006993   .0588969     0.12   0.905    -.1084428    .1224289
   cp_hasPriorI |    .029969   .0381666     0.79   0.432    -.0448362    .1047743
 cp_ever_ac_sol |    .029775   .0278262     1.07   0.285    -.0247633    .0843133
     cp_3charge |  -.0161464   .0245468    -0.66   0.511    -.0642572    .0319644
        cp_rsth |    .032276   .0196059     1.65   0.100    -.0061509    .0707029
    cp_p_medlim |  -.0128722   .0302948    -0.42   0.671    -.0722489    .0465045
    cp_p_hsgrad |  -.0475792   .0322371    -1.48   0.140    -.1107628    .0156044
   cp_p_had_job |   .0017759    .023104     0.08   0.939    -.0435071    .0470588
cp_p_prob_drugalc |    -.03418   .0502955    -0.68   0.497    -.1327573    .0643973
   cp_p_prob_mh |  -.0058931   .0229453    -0.26   0.797     -.050865    .0390787
     cp_p_usvet |  -.0016024   .0449611    -0.04   0.972    -.0897245    .0865198
        cp_p_iq |  -.0001858   .0007623    -0.24   0.807    -.0016799    .0013083
 cp_18under_1arr |  -.0635647   .0384577    -1.65   0.098    -.1389405     .011811
         cp_apv |  -.0441763   .0507805    -0.87   0.384    -.1437044    .0553517
      stretches |  -.0091764   .0089576    -1.02   0.306     -.026733    .0083802
     r_time2rel |   .0000327   .0000285     1.15   0.250    -.0000231    .0000885
     r_staytime |  -.0000739   .0000345    -2.14   0.032    -.0001415   -6.36e-06
     tier_tt_fa |    .013782   .0123344     1.12   0.264    -.0103929    .0379569
              k |   .0495105   .0274148     1.81   0.071    -.0042214    .1032424
          _cons |    .599387   .1332322     4.50   0.000     .3382568    .8605173
----------------+----------------------------------------------------------------
Mills           |
      rho1-rho0 |  -.0828313   .0384575    -2.15   0.031    -.1582066    -.007456
----------------+----------------------------------------------------------------
ATE             |
     E(Y1-Y0)@X |  -.0222557   .0310893    -0.72   0.474    -.0831896    .0386781
---------------------------------------------------------------------------------
(note: file mte_base_t180_has_postA.gph not found)
(file mte_base_t180_has_postA.gph saved)
(running parametric_polynomial on estimation sample)
```

Outcome Model #2: An example of margte Output for Recidivism.

```
Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                      Number of obs      =     10131
Treatment Model: Probit                          Replications       =        50
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
   has_post0 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Treated      |
 c_hasPriorI |    .028913    .0156611     1.85   0.065    -.0017822    .0596083
  r_pri_narr |   .0154265     .001831     8.43   0.000     .0118378    .0190153
rel_pri_narr |   .0000344    .0013257     0.03   0.979    -.0025639    .0026327
      r_rsth |   .0620925    .0112046     5.54   0.000     .0401319    .0840531
    rel_rsth |   .0036203    .0076715     0.47   0.637    -.0114156    .0186561
       r_age |  -.0071681    .0010227    -7.01   0.000    -.0091727   -.0051636
     r_black |   .0279548    .0219691     1.27   0.203    -.0151038    .0710135
   r_married |  -.0091492    .0168723    -0.54   0.588    -.0422184      .02392
     r_islam |   .0614632    .0179309     3.43   0.001     .0263194    .0966071
     r_urban |  -.0206128    .0148434    -1.39   0.165    -.0497052    .0084797
   r_maxsent |  -.0001941    .0002013    -0.96   0.335    -.0005886    .0002004
  r_cust_gt3 |   .0434974    .0151569     2.87   0.004     .0137903    .0732044
     r_misAB |  -.0323351    .0209164    -1.55   0.122    -.0733305    .0086603
     r_hadtc |   .0719526    .0256729     2.80   0.005     .0216346    .1222706
r_ever_ac_sol |  -.0119599     .018001    -0.66   0.506    -.0472411    .0233213
   r_3charge |   .0149584    .0114587     1.31   0.192    -.0075002    .0374171
```

r_p_medlim	-.0186877	.0137839	-1.36	0.175	-.0457037	.0083283
r_p_hsgrad	-.0880585	.0160449	-5.49	0.000	-.1195059	-.0566111
r_p_had_job	.0269436	.0137639	1.96	0.050	-.0000331	.0539203
r_p_prob_drugalc	.0130367	.0232835	0.56	0.576	-.0325982	.0586716
r_p_prob_mh	.0644291	.0117151	5.50	0.000	.041468	.0873903
r_p_usvet	-.0253462	.0302892	-0.84	0.403	-.0847119	.0340196
r_p_iq	.0005291	.0004539	1.17	0.244	-.0003606	.0014188
r_18under_1arr	-.056087	.0182028	-3.08	0.002	-.0917638	-.0204102
c_age	-.000742	.0009437	-0.79	0.432	-.0025916	.0011076
c_black	.0167276	.019479	0.86	0.390	-.0214504	.0549057
c_married	-.013691	.0179484	-0.76	0.446	-.0488691	.0214872
c_islam	-.0093486	.0161653	-0.58	0.563	-.0410319	.0223347
c_urban	-.0020642	.0135358	-0.15	0.879	-.028594	.0244656
c_maxsent	-.0000847	.0000364	-2.33	0.020	-.0001561	-.0000134
c_cust_gt3	-.0113921	.0131178	-0.87	0.385	-.0371024	.0143182
c_misAB	.0107365	.0133972	0.80	0.423	-.0155216	.0369946
c_hadtc	-.0557084	.0199824	-2.79	0.005	-.0948731	-.0165437
c_ever_ac_sol	.0097991	.0111422	0.88	0.379	-.0120393	.0316374
c_3charge	.0075835	.0105308	0.72	0.471	-.0130564	.0282235
c_p_medlim	.000241	.014799	0.02	0.987	-.0287645	.0292465
c_p_hsgrad	.0010954	.015611	0.07	0.944	-.0295017	.0316924
c_p_had_job	.008539	.0117961	0.72	0.469	-.014581	.031659
c_p_prob_drugalc	.0030671	.0193442	0.16	0.874	-.0348469	.0409812
c_p_prob_mh	-.0083276	.0126805	-0.66	0.511	-.0331809	.0165258
c_p_usvet	.010665	.0236883	0.45	0.653	-.0357632	.0570931
c_p_iq	-.0005422	.0004411	-1.23	0.219	-.0014067	.0003223
c_18under_1arr	.0073819	.0168448	0.44	0.661	-.0256333	.0403971
c_apv	-.0050657	.0187156	-0.27	0.787	-.0417476	.0316161
cp_age	-.0040109	.0022413	-1.79	0.074	-.0084038	.0003819
cp_black	.0213391	.0319124	0.67	0.504	-.041208	.0838861
cp_married	-.0460766	.0360956	-1.28	0.202	-.1168226	.0246694
cp_islam	.0035186	.0371983	0.09	0.925	-.0693888	.0764259
cp_urban	-.0187659	.0282029	-0.67	0.506	-.0740426	.0365108
cp_maxsent	.0000991	.0000835	1.19	0.235	-.0000645	.0002628
cp_pri_narr	.0022712	.003131	0.73	0.468	-.0038655	.0084079
cp_cust_gt3	.0413539	.0331545	1.25	0.212	-.0236278	.1063355
cp_misAB	-.0096793	.044531	-0.22	0.828	-.0969584	.0775998
cp_hadtc	-.0549571	.0548348	-1.00	0.316	-.1624313	.0525171
cp_hasPriorI	-.0331093	.0396981	-0.83	0.404	-.1109162	.0446977
cp_ever_ac_sol	.040574	.0367674	1.10	0.270	-.0314887	.1126367
cp_3charge	.0382399	.0270854	1.41	0.158	-.0148465	.0913262
cp_rsth	-.0250824	.022728	-1.10	0.270	-.0696284	.0194636
cp_p_medlim	-.0282949	.0335198	-0.84	0.399	-.0939925	.0374027
cp_p_hsgrad	.0199641	.0353193	0.57	0.572	-.0492604	.0891887
cp_p_had_job	-.0010438	.0264525	-0.04	0.969	-.0528897	.050802
cp_p_prob_drugalc	-.0030689	.0423329	-0.07	0.942	-.0860398	.079902
cp_p_prob_mh	.0102191	.0260928	0.39	0.695	-.0409218	.06136
cp_p_usvet	-.0570882	.0620861	-0.92	0.358	-.1787746	.0645983
cp_p_iq	.0000491	.0010525	0.05	0.963	-.0020137	.002112
cp_18under_1arr	.0534426	.0452631	1.18	0.238	-.0352713	.1421566
cp_apv	.0919411	.050867	1.81	0.071	-.0077564	.1916385
stretches	-.0026757	.0050448	-0.53	0.596	-.0125634	.0072119
r_time2rel	2.31e-06	.0000223	0.10	0.917	-.0000413	.000046
r_staytime	-.0000474	.0000219	-2.17	0.030	-.0000903	-4.53e-06
tier_tt_fa	.0254073	.0119755	2.12	0.034	.0019358	.0488788
k	-.0184361	.0238829	-0.77	0.440	-.0652456	.0283735
_cons	.7525316	.1560228	4.82	0.000	.4467325	1.058331
Untreated						
c_hasPriorI	-.003381	.0194064	-0.17	0.862	-.0414169	.0346548
r_pri_narr	.0118089	.0028158	4.19	0.000	.0062901	.0173277
rel_pri_narr	.0011456	.0019815	0.58	0.563	-.0027381	.0050294
r_rsth	.0859918	.0154977	5.55	0.000	.0556168	.1163668
rel_rsth	.004204	.0110365	0.38	0.703	-.0174271	.0258351
r_age	-.0065711	.0012155	-5.41	0.000	-.0089535	-.0041887
r_black	.0485316	.0187975	2.58	0.010	.0116891	.0853741
r_married	-.0412124	.0179496	-2.30	0.022	-.0763931	-.0060318
r_islam	.0563769	.0202661	2.78	0.005	.0166561	.0960978
r_urban	-.0076699	.0160518	-0.48	0.633	-.0391308	.023791
r_maxsent	-.0003323	.0003465	-0.96	0.338	-.0010113	.0003468
r_cust_gt3	.0111354	.0178961	0.62	0.534	-.0239404	.0462112
r_misAB	-.0304151	.0259928	-1.17	0.242	-.0813601	.0205299
r_hadtc	-.026803	.0489844	-0.55	0.584	-.1228107	.0692046
r_ever_ac_sol	.0255799	.0271053	0.94	0.345	-.0275455	.0787053
r_3charge	.0220275	.0140787	1.56	0.118	-.0055662	.0496211
r_p_medlim	.0030144	.0196732	0.15	0.878	-.0355443	.0415731
r_p_hsgrad	-.1110414	.0147063	-7.55	0.000	-.1398652	-.0822177
r_p_had_job	.0065133	.0155318	0.42	0.675	-.0239284	.0369551
r_p_prob_drugalc	-.0269391	.0307901	-0.87	0.382	-.0872866	.0334084
r_p_prob_mh	.0847424	.0170112	4.98	0.000	.0514012	.1180837
r_p_usvet	-.0196382	.0368344	-0.53	0.594	-.0918322	.0525558
r_p_iq	-.0001643	.0004466	-0.37	0.713	-.0010396	.0007109
r_18under_1arr	-.0790928	.0222124	-3.56	0.000	-.1226283	-.0355573
c_age	-.0012238	.001043	-1.17	0.241	-.003268	.0008205
c_black	-.0115068	.0225515	-0.51	0.610	-.055707	.0326933
c_married	.0014066	.0176961	0.08	0.937	-.0332772	.0360903
c_islam	-.0009284	.0250695	-0.04	0.970	-.0500637	.0482069
c_urban	-.005842	.0186882	-0.31	0.755	-.0424701	.0307861
c_maxsent	-.000027	.0000507	-0.53	0.594	-.0001263	.0000723

```
      c_cust_gt3 |    .008266   .0151463     0.55   0.585    -.0214203    .0379522
         c_misAB |    -.02366   .0214309    -1.10   0.270    -.0656638    .0183438
         c_hadtc |   .0264611   .0359352     0.74   0.462    -.0439706    .0968929
   c_ever_ac_sol |   .0378529   .0166331     2.28   0.023     .0052526    .0704532
       c_3charge |   .0168477   .0127109     1.33   0.185    -.0080651    .0417605
      c_p_medlim |   .0001677   .0182364     0.01   0.993     -.035575    .0359103
      c_p_hsgrad |  -.0150418   .0168728    -0.89   0.373    -.0481118    .0180282
     c_p_had_job |   .0057463    .014225     0.40   0.686    -.0221341    .0336268
 c_p_prob_drugalc |   .0276335   .0327098     0.84   0.398    -.0364765    .0917435
     c_p_prob_mh |   .0112581   .0141858     0.79   0.427    -.0165455    .0390617
       c_p_usvet |  -.0104614   .0254914    -0.41   0.682    -.0604236    .0395008
          c_p_iq |  -.0000893    .000383    -0.23   0.816    -.0008399    .0006612
   c_18under_1arr |  -.0090331   .0199902    -0.45   0.651    -.0482133    .0301471
           c_apv |   .0197811   .0254891     0.78   0.438    -.0301767    .0697389
          cp_age |  -.0031074   .0017608    -1.76   0.078    -.0065586    .0003438
        cp_black |  -.0435452   .0302509    -1.44   0.150     -.102836    .0157455
      cp_married |   .0266155   .0441083     0.60   0.546    -.0598353    .1130662
        cp_islam |   .0456647   .0405536     1.13   0.260     -.033819    .1251483
        cp_urban |  -.0445164   .0368644    -1.21   0.227    -.1167692    .0277364
      cp_maxsent |  -.0000361    .000112    -0.32   0.747    -.0002557    .0001834
     cp_pri_narr |    .002705   .0031846     0.85   0.396    -.0035368    .0089467
     cp_cust_gt3 |   .0303384   .0342753     0.89   0.376      -.03684    .0975168
        cp_misAB |  -.0289734   .0426827    -0.68   0.497    -.1126299    .0546831
        cp_hadtc |  -.0138788   .0724075    -0.19   0.848    -.1557949    .1280373
     cp_hasPriorI |   .0210644   .0455812     0.46   0.644    -.0682731    .1104019
   cp_ever_ac_sol |    .046005   .0383696     1.20   0.231     -.029198     .121208
      cp_3charge |   .0216302     .02518     0.86   0.390    -.0277217     .070982
         cp_rsth |   .0349012    .021327     1.64   0.102    -.0068989    .0767013
     cp_p_medlim |  -.0046864   .0368961    -0.13   0.899    -.0770015    .0676287
     cp_p_hsgrad |  -.0286359    .034199    -0.84   0.402    -.0956647    .0383929
    cp_p_had_job |  -.0079373   .0257461    -0.31   0.758    -.0583987    .0425241
cp_p_prob_drugalc |  -.0492445   .0612557    -0.80   0.421    -.1693035    .0708145
    cp_p_prob_mh |  -.0236532   .0289934    -0.82   0.415    -.0804792    .0331728
      cp_p_usvet |   .0400679   .0539387     0.74   0.458    -.0656501    .1457858
         cp_p_iq |  -.0006841   .0008959    -0.76   0.445    -.0024401    .0010719
  cp_18under_1arr |  -.0665253   .0451289    -1.47   0.140    -.1549763    .0219257
          cp_apv |  -.0675966    .048551    -1.39   0.164    -.1627549    .0275617
       stretches |  -.0137384   .0126701    -1.08   0.278    -.0385714    .0110945
      r_time2rel |   .0000393   .0000458     0.86   0.391    -.0000505    .0001291
      r_staytime |  -.0001543   .0000492    -3.14   0.002    -.0002507    -.000058
      tier_tt_fa |  -.0007112    .012963    -0.05   0.956    -.0261182    .0246958
               k |   .0533753   .0222577     2.40   0.016     .0097511    .0969995
           _cons |   .7281429   .1861438     3.91   0.000     .3633077    1.092978
-----------------+----------------------------------------------------------------
Mills            |
       rho1-rho0 |  -.0718113   .0320574    -2.24   0.025    -.1346427     -.00898
-----------------+----------------------------------------------------------------
ATE              |
      E(Y1-Y0)@X |   .0392658   .0279424     1.41   0.160    -.0155003    .0940319
----------------------------------------------------------------------------------
(note: file mte_base_t120_has_post0.gph not found)
(file mte_base_t120_has_post0.gph saved)
(running parametric_polynomial on estimation sample)

Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                       Number of obs      =     10131
Treatment Model: Probit                           Replications       =        50
----------------------------------------------------------------------------------
                 |   Observed   Bootstrap                         Normal-based
       has_post0 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
Treated          |
     c_hasPriorI |    .021173   .0189066     1.12   0.263    -.0158832    .0582292
      r_pri_narr |   .0160466   .0026627     6.03   0.000     .0108278    .0212654
    rel_pri_narr |   .0002759   .0019436     0.14   0.887    -.0035335    .0040854
          r_rsth |   .0642891   .0168769     3.81   0.000     .0312109    .0973672
        rel_rsth |  -.0001773   .0109259    -0.02   0.987    -.0215916     .021237
           r_age |  -.0068159    .000972    -7.01   0.000    -.0087209   -.0049109
         r_black |   .0384029   .0324446     1.18   0.237    -.0251874    .1019932
       r_married |   -.003389   .0200436    -0.17   0.866    -.0426738    .0358958
         r_islam |   .0579052   .0159101     3.64   0.000     .0267219    .0890884
         r_urban |  -.0200424    .017197    -1.17   0.244    -.0537479    .0136631
       r_maxsent |  -.0002608    .000204    -1.28   0.201    -.0006606     .000139
      r_cust_gt3 |   .0566148   .0127154     4.45   0.000     .0316932    .0815365
         r_misAB |  -.0422695   .0177778    -2.38   0.017    -.0771133   -.0074257
         r_hadtc |   .0803803   .0309604     2.60   0.009      .019699    .1410615
   r_ever_ac_sol |  -.0265767   .0165184    -1.61   0.108    -.0589522    .0057988
       r_3charge |   .0164285   .0125971     1.30   0.192    -.0082614    .0411184
      r_p_medlim |  -.0190234   .0190882    -1.00   0.319    -.0564355    .0183888
      r_p_hsgrad |    -.08696   .0201364    -4.32   0.000    -.1264267   -.0474933
     r_p_had_job |   .0293948   .0152278     1.93   0.054    -.0004511    .0592407
 r_p_prob_drugalc |   .0048438   .0239312     0.20   0.840    -.0420606    .0517481
     r_p_prob_mh |   .0661975   .0136235     4.86   0.000      .039496     .092899
       r_p_usvet |  -.0467454   .0266394    -1.75   0.079    -.0989576    .0054669
          r_p_iq |   .0002012   .0005234     0.38   0.701    -.0008247    .0012272
   r_18under_1arr |  -.0646008   .0238671    -2.71   0.007    -.1113795   -.0178221
```

c_age	-.0007539	.001249	-0.60	0.546	-.0032018	.001694
c_black	.0009691	.0191729	0.05	0.960	-.0366091	.0385472
c_married	-.0274921	.0179565	-1.53	0.126	-.0626862	.007702
c_islam	.0052431	.0184923	0.28	0.777	-.0310011	.0414874
c_urban	.0080004	.0177595	0.45	0.652	-.0268076	.0428084
c_maxsent	-.0000843	.0000472	-1.79	0.074	-.0001768	8.23e-06
c_cust_gt3	-.0066065	.0153352	-0.43	0.667	-.036663	.0234499
c_misAB	.0161496	.0158393	1.02	0.308	-.0148949	.0471941
c_hadtc	-.0684482	.0322151	-2.12	0.034	-.1315886	-.0053078
c_ever_ac_sol	.0052466	.0156779	0.33	0.738	-.0254814	.0359747
c_3charge	.0048023	.0132318	0.36	0.717	-.0211315	.0307362
c_p_medlim	.0040712	.0124504	0.33	0.744	-.0203312	.0284736
c_p_hsgrad	.0005899	.018364	0.03	0.974	-.0354028	.0365827
c_p_had_job	.0140461	.0113434	1.24	0.216	-.0081865	.0362788
c_p_prob_drugalc	.0054151	.0258608	0.21	0.834	-.045271	.0561013
c_p_prob_mh	-.0077159	.0132338	-0.58	0.560	-.0336538	.0182219
c_p_usvet	.0099322	.0262878	0.38	0.706	-.0415909	.0614553
c_p_iq	-.0005046	.0005262	-0.96	0.338	-.0015359	.0005268
c_18under_1arr	.0055544	.0181463	0.31	0.760	-.0300117	.0411206
c_apv	.0014535	.0193479	0.08	0.940	-.0364677	.0393747
cp_age	-.0034908	.0022551	-1.55	0.122	-.0079108	.0009292
cp_black	.0120855	.0355291	0.34	0.734	-.0575502	.0817212
cp_married	-.0154306	.0363069	-0.43	0.671	-.0865908	.0557295
cp_islam	.0019231	.0426475	0.05	0.964	-.0816645	.0855107
cp_urban	-.0231416	.0330181	-0.70	0.483	-.087856	.0415728
cp_maxsent	.0000834	.000139	0.60	0.548	-.000189	.0003559
cp_pri_narr	.0020324	.0038004	0.53	0.593	-.0054162	.009481
cp_cust_gt3	.0220707	.0313575	0.70	0.482	-.0393888	.0835303
cp_misAB	-.0425794	.040532	-1.05	0.293	-.1220207	.0368619
cp_hadtc	-.0825073	.0607349	-1.36	0.174	-.2015455	.0365309
cp_hasPriorI	-.0575658	.0447697	-1.29	0.199	-.1453128	.0301812
cp_ever_ac_sol	.0674209	.0366823	1.84	0.066	-.0044751	.1393168
cp_3charge	.0518731	.0272584	1.90	0.057	-.0015524	.1052986
cp_rsth	-.0142093	.0261963	-0.54	0.588	-.0655531	.0371344
cp_p_medlim	-.0187583	.0343216	-0.55	0.585	-.0860274	.0485108
cp_p_hsgrad	.0060842	.0415968	0.15	0.884	-.0754441	.0876124
cp_p_had_job	-.0320843	.0265492	-1.21	0.227	-.0841197	.0199511
cp_p_prob_drugalc	-.0090056	.0669063	-0.13	0.893	-.1401396	.1221284
cp_p_prob_mh	.0172748	.0295725	0.58	0.559	-.0406862	.0752357
cp_p_usvet	-.0380228	.0585835	-0.65	0.516	-.1528444	.0767988
cp_p_iq	.0005038	.0010525	0.48	0.632	-.001559	.0025666
cp_18under_1arr	.0576242	.0408516	1.41	0.158	-.0224434	.1376919
cp_apv	.0936572	.0526017	1.78	0.075	-.0094403	.1967548
stretches	-.001764	.0048067	-0.37	0.714	-.011185	.0076569
r_time2rel	-6.28e-06	.0000254	-0.25	0.805	-.0000562	.0000436
r_staytime	-.0000232	.0000226	-1.02	0.306	-.0000676	.0000212
tier_tt_fa	.0292808	.0138356	2.12	0.034	.0021635	.0563981
k	-.0259293	.0223631	-1.16	0.246	-.0697601	.0179016
_cons	.6559535	.1883922	3.48	0.000	.2867116	1.025195
Untreated						
c_hasPriorI	.0124825	.018039	0.69	0.489	-.0228733	.0478384
r_pri_narr	.0122971	.0020212	6.08	0.000	.0083356	.0162585
rel_pri_narr	.000702	.0014095	0.50	0.618	-.0020605	.0034645
r_rsth	.0791452	.0112522	7.03	0.000	.0570912	.1011991
rel_rsth	.0077361	.0088262	0.88	0.381	-.009563	.0250353
r_age	-.0071785	.0009886	-7.26	0.000	-.0091161	-.0052408
r_black	.0443221	.0179987	2.46	0.014	.0090453	.0795988
r_married	-.0404313	.0153787	-2.63	0.009	-.070573	-.0102896
r_islam	.0609182	.0183271	3.32	0.001	.0249979	.0968386
r_urban	-.0087669	.0119277	-0.74	0.462	-.0321448	.014611
r_maxsent	-.0001807	.0002767	-0.65	0.514	-.000723	.0003617
r_cust_gt3	.0046241	.0175616	0.26	0.792	-.029796	.0390442
r_misAB	-.021297	.0205767	-1.04	0.301	-.0616266	.0190326
r_hadtc	.0077256	.0494317	0.16	0.876	-.0891587	.1046099
r_ever_ac_sol	.0359484	.0230566	1.56	0.119	-.0092416	.0811385
r_3charge	.0199451	.0105217	1.90	0.058	-.0006771	.0405673
r_p_medlim	-.0036103	.0165316	-0.22	0.827	-.0360116	.0287911
r_p_hsgrad	-.1076189	.0167349	-6.43	0.000	-.1404188	-.0748191
r_p_had_job	.0073484	.0158349	0.46	0.643	-.0236874	.0383842
r_p_prob_drugalc	-.01386	.0257339	-0.54	0.590	-.0642975	.0365774
r_p_prob_mh	.0796266	.0117446	6.78	0.000	.0566077	.1026456
r_p_usvet	.0038599	.0312182	0.12	0.902	-.0573267	.0650465
r_p_iq	.0002878	.000474	0.61	0.544	-.0006413	.0012168
r_18under_1arr	-.0685571	.0196098	-3.50	0.000	-.1069915	-.0301227
c_age	-.0011623	.000972	-1.20	0.232	-.0030673	.0007428
c_black	.0052128	.0145994	0.36	0.721	-.0234015	.0338271
c_married	.0131469	.015643	0.84	0.401	-.0175129	.0438067
c_islam	-.0158125	.0188895	-0.84	0.403	-.0528351	.0212102
c_urban	-.0132318	.0154053	-0.86	0.390	-.0434257	.016962
c_maxsent	-.0000307	.0000466	-0.66	0.511	-.0001221	.0000608
c_cust_gt3	.0018267	.0146804	0.12	0.901	-.0269463	.0305997
c_misAB	-.0181906	.016719	-1.09	0.277	-.0509592	.014578
c_hadtc	.0251271	.033595	0.75	0.454	-.040718	.0909721
c_ever_ac_sol	.0372348	.0150924	2.47	0.014	.0076542	.0668155
c_3charge	.0169609	.0116436	1.46	0.145	-.00586	.0397819
c_p_medlim	-.0024093	.0162653	-0.15	0.882	-.0342887	.0294702
c_p_hsgrad	-.0146843	.0118743	-1.24	0.216	-.0379575	.0085888
c_p_had_job	-.0010798	.0141964	-0.08	0.939	-.0289043	.0267446

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  c_p_prob_drugalc |   .0224779   .0274072     0.82   0.412    -.0312393     .076195
      c_p_prob_mh |   .0059805   .0129782     0.46   0.645    -.0194563    .0314173
         c_p_usvet |  -.0027641   .0290227    -0.10   0.924    -.0596476    .0541193
            c_p_iq |  -.0001672   .0004112    -0.41   0.684    -.0009731    .0006388
   c_18under_1arr |  -.0061623   .0165303    -0.37   0.709    -.0385612    .0262365
            c_apv |   .0054105   .0231504     0.23   0.815    -.0399634    .0507845
            cp_age |  -.0036103   .0014892    -2.42   0.015    -.0065291   -.0006914
          cp_black |  -.0272057   .0274009    -0.99   0.321    -.0809104    .0264991
        cp_married |  -.0021985    .042716    -0.05   0.959    -.0859204    .0815234
          cp_islam |   .0385546   .0377203     1.02   0.307    -.0353757     .112485
          cp_urban |   -.034942   .0273699    -1.28   0.202     -.088586    .0187019
        cp_maxsent |  -4.29e-06   .0000952    -0.05   0.964    -.0001908    .0001822
       cp_pri_narr |   .0025695   .0027304     0.94   0.347     -.002782     .007921
       cp_cust_gt3 |   .0490449   .0256161     1.91   0.056    -.0011617    .0992515
          cp_misAB |   .0016583   .0289876     0.06   0.954    -.0551563    .0584729
          cp_hadtc |  -.0103481   .0799638    -0.13   0.897    -.1670743    .1463781
      cp_hasPriorI |   .0334286    .040834     0.82   0.413    -.0466046    .1134617
    cp_ever_ac_sol |   .0185126   .0364885     0.51   0.612    -.0530035    .0900287
        cp_3charge |   .0097203   .0262456     0.37   0.711    -.0417201    .0611608
           cp_rsth |   .0172536   .0151243     1.14   0.254    -.0123895    .0468967
       cp_p_medlim |  -.0108352   .0293137    -0.37   0.712    -.0682889    .0466185
       cp_p_hsgrad |   -.010445   .0311855    -0.33   0.738    -.0715674    .0506774
      cp_p_had_job |   .0159035   .0272213     0.58   0.559    -.0374493    .0692563
 cp_p_prob_drugalc |  -.0362996   .0422567    -0.86   0.390    -.1191212     .046522
      cp_p_prob_mh |  -.0255962    .025538    -1.00   0.316    -.0756497    .0244573
        cp_p_usvet |   .0135122   .0521152     0.26   0.795    -.0886318    .1156561
           cp_p_iq |  -.0006891   .0008662    -0.80   0.426    -.0023868    .0010086
  cp_18under_1arr |  -.0484854   .0324757    -1.49   0.135    -.1121366    .0151658
            cp_apv |  -.0426032   .0460709    -0.92   0.355    -.1329004    .0476941
         stretches |  -.0143292   .0090504    -1.58   0.113    -.0320677    .0034093
        r_time2rel |   .0000201   .0000369     0.55   0.586    -.0000522    .0000925
        r_staytime |  -.0001396     .00004    -3.49   0.000     -.000218   -.0000611
        tier_tt_fa |   .0019808    .012604     0.16   0.875    -.0227227    .0266842
                 k |   .0438113   .0233888     1.87   0.061    -.0020298    .0896525
             _cons |   .7752169   .1309258     5.92   0.000     .5186071    1.031827
-----------------+----------------------------------------------------------------
Mills            |
        rho1-rho0 |  -.0697406   .0343076    -2.03   0.042    -.1369822    -.002499
-----------------+----------------------------------------------------------------
ATE              |
       E(Y1-Y0)@X |   .0093557   .0228201     0.41   0.682    -.0353709    .0540822
----------------------------------------------------------------------------------
(note: file mte_base_t150_has_post0.gph not found)
(file mte_base_t150_has_post0.gph saved)
(running parametric_polynomial on estimation sample)


Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                         Number of obs      =     10131
Treatment Model: Probit                             Replications       =        50
----------------------------------------------------------------------------------
                 |   Observed   Bootstrap                         Normal-based
        has_post0 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
Treated          |
      c_hasPriorI |   .0121651   .0218267     0.56   0.577    -.0306145    .0549447
       r_pri_narr |   .0155668   .0024446     6.37   0.000     .0107753    .0203582
     rel_pri_narr |   .0000965   .0018236     0.05   0.958    -.0034776    .0036706
           r_rsth |   .0700382   .0161775     4.33   0.000     .0383309    .1017454
         rel_rsth |    .003403   .0118507     0.29   0.774     -.019824      .02663
            r_age |  -.0068869   .0012912    -5.33   0.000    -.0094176   -.0043562
          r_black |   .0366714    .036104     1.02   0.310    -.0340912    .1074339
        r_married |  -.0175876   .0226706    -0.78   0.438    -.0620211    .0268459
          r_islam |   .0544862   .0189523     2.87   0.004     .0173404    .0916319
          r_urban |  -.0187866   .0171933    -1.09   0.275     -.052485    .0149117
        r_maxsent |  -.0003992   .0002054    -1.94   0.052    -.0008018    3.35e-06
      r_cust_gt3 |   .0684537    .013346     5.13   0.000     .042296    .0946114
          r_misAB |  -.0443084   .0169884    -2.61   0.009     -.077605   -.0110119
          r_hadtc |   .0780865   .0301424     2.59   0.010     .0190085    .1371645
    r_ever_ac_sol |    -.01045   .0220748    -0.47   0.636    -.0537159    .0328158
        r_3charge |   .0296483   .0111742     2.65   0.008     .0077472    .0515494
      r_p_medlim |  -.0095457   .0186518    -0.51   0.609    -.0461025    .0270111
      r_p_hsgrad |  -.0966286   .0160416    -6.02   0.000    -.1280695   -.0651877
     r_p_had_job |   .0356864   .0112414     3.17   0.002     .0136536    .0577193
 r_p_prob_drugalc |  -.0160127   .0243777    -0.66   0.511    -.0637922    .0317668
     r_p_prob_mh |   .0625979   .0156265     4.01   0.000     .0319706    .0932252
       r_p_usvet |  -.0318052   .0389254    -0.82   0.414    -.1080976    .0444873
          r_p_iq |   6.01e-06   .0005639     0.01   0.991    -.0010993    .0011113
  r_18under_1arr |  -.0636009   .0226435    -2.81   0.005    -.1079814   -.0192203
            c_age |  -.0010867   .0010977    -0.99   0.322    -.0032382    .0010648
          c_black |  -.0047169   .0235831    -0.20   0.841     -.050939    .0415052
        c_married |  -.0297288   .0177892    -1.67   0.095    -.0645949    .0051373
          c_islam |   -.005965   .0222132    -0.27   0.788    -.0495022    .0375721
          c_urban |   .0252401    .021221     1.19   0.234    -.0163523    .0668325
        c_maxsent |  -.0000449   .0000438    -1.03   0.304    -.0001307    .0000408
      c_cust_gt3 |  -.0037436   .0194411    -0.19   0.847    -.0418475    .0343603
```

c_misAB	.0077209	.0209436	0.37	0.712	-.0333278	.0487696
c_hadtc	-.0642478	.0258003	-2.49	0.013	-.1148154	-.0136801
c_ever_ac_sol	-.0040827	.016219	-0.25	0.801	-.0358715	.027706
c_3charge	.009897	.0140626	0.70	0.482	-.0176653	.0374593
c_p_medlim	-.0008889	.0170992	-0.05	0.959	-.0344026	.0326249
c_p_hsgrad	-.0068218	.0181749	-0.38	0.707	-.0424439	.0288003
c_p_had_job	.0135656	.0145884	0.93	0.352	-.0150271	.0421583
c_p_prob_drugalc	.007154	.0308927	0.23	0.817	-.0533946	.0677026
c_p_prob_mh	-.002518	.0142891	-0.18	0.860	-.0305241	.0254881
c_p_usvet	.0081567	.0298279	0.27	0.785	-.0503049	.0666182
c_p_iq	-.0003532	.0005607	-0.63	0.529	-.001452	.0007457
c_18under_1arr	-.0069863	.0234197	-0.30	0.765	-.0528881	.0389155
c_apv	.0074662	.0280605	0.27	0.790	-.0475313	.0624637
cp_age	-.0047015	.0024983	-1.88	0.060	-.009598	.000195
cp_black	.0128043	.0437561	0.29	0.770	-.0729561	.0985646
cp_married	-.0438297	.047553	-0.92	0.357	-.1370318	.0493724
cp_islam	.0216448	.0390671	0.55	0.580	-.0549253	.0982149
cp_urban	-.0239538	.0350821	-0.68	0.495	-.0927134	.0448057
cp_maxsent	.0001979	.0001122	1.76	0.078	-.0000219	.0004178
cp_pri_narr	.0042454	.0041952	1.01	0.312	-.003977	.0124677
cp_cust_gt3	.0208057	.0262493	0.79	0.428	-.030642	.0722534
cp_misAB	-.0158691	.0413346	-0.38	0.701	-.0968834	.0651452
cp_hadtc	-.0810373	.0659133	-1.23	0.219	-.210225	.0481505
cp_hasPriorI	-.040007	.0482166	-0.83	0.407	-.1345097	.0544958
cp_ever_ac_sol	.0409425	.0437729	0.94	0.350	-.0448509	.1267358
cp_3charge	.0427453	.032114	1.33	0.183	-.0201969	.1056875
cp_rsth	-.0353027	.0231719	-1.52	0.128	-.0807188	.0101135
cp_p_medlim	-.0272452	.0385791	-0.71	0.480	-.1028589	.0483686
cp_p_hsgrad	.0392892	.0410221	0.96	0.338	-.0411127	.1196911
cp_p_had_job	-.0167772	.0377816	-0.44	0.657	-.0908278	.0572734
cp_p_prob_drugalc	.002299	.0682837	0.03	0.973	-.1315347	.1361327
cp_p_prob_mh	.0252743	.0342215	0.74	0.460	-.0417986	.0923472
cp_p_usvet	.0266857	.0723862	0.37	0.712	-.1151887	.1685602
cp_p_iq	-.0003321	.0011076	-0.30	0.764	-.0025029	.0018386
cp_18under_1arr	.0852268	.0497782	1.71	0.087	-.0123367	.1827903
cp_apv	.0926251	.0684982	1.35	0.176	-.0416288	.2268791
stretches	-.0040786	.0052659	-0.77	0.439	-.0143996	.0062424
r_time2rel	-9.66e-06	.0000267	-0.36	0.718	-.0000621	.0000427
r_staytime	-.000014	.0000311	-0.45	0.653	-.0000749	.000047
tier_tt_fa	.0361013	.014906	2.42	0.015	.0068861	.0653165
k	-.025693	.0276723	-0.93	0.353	-.0799297	.0285437
_cons	.7842553	.1855676	4.23	0.000	.4205494	1.147961
Untreated						
c_hasPriorI	.0214424	.0175767	1.22	0.222	-.0130073	.0558922
r_pri_narr	.0134105	.0016488	8.13	0.000	.0101789	.0166422
rel_pri_narr	.000934	.0010314	0.91	0.365	-.0010875	.0029555
r_rsth	.0723526	.0102771	7.04	0.000	.0522099	.0924953
rel_rsth	.0033341	.007057	0.47	0.637	-.0104974	.0171656
r_age	-.0070661	.0009895	-7.14	0.000	-.0090056	-.0051267
r_black	.0460885	.0160074	2.88	0.004	.0147144	.0774625
r_married	-.0245843	.01577	-1.56	0.119	-.0554929	.0063243
r_islam	.0634383	.0157086	4.04	0.000	.03265	.0942267
r_urban	-.0133902	.0154121	-0.87	0.385	-.0435972	.0168169
r_maxsent	-.000034	.0002209	-0.15	0.878	-.0004668	.0003989
r_cust_gt3	.0073534	.0145624	0.50	0.614	-.0211884	.0358952
r_misAB	-.0288302	.0135627	-2.13	0.034	-.0554126	-.0022478
r_hadtc	.0206354	.0377861	0.55	0.585	-.053424	.0946947
r_ever_ac_sol	.0128734	.026502	0.49	0.627	-.0390696	.0648163
r_3charge	.0097503	.0104284	0.93	0.350	-.0106889	.0301896
r_p_medlim	-.0120969	.0142669	-0.85	0.396	-.0400595	.0158657
r_p_hsgrad	-.098308	.0169413	-5.80	0.000	-.1315123	-.0651037
r_p_had_job	.0094691	.0130565	0.73	0.468	-.0161212	.0350593
r_p_prob_drugalc	.0057383	.0245518	0.23	0.815	-.0423825	.053859
r_p_prob_mh	.0810487	.0110233	7.35	0.000	.0594433	.102654
r_p_usvet	-.0135174	.0253031	-0.53	0.593	-.0631105	.0360758
r_p_iq	.0003787	.0004252	0.89	0.373	-.0004547	.0012121
r_18under_1arr	-.0666495	.0144409	-4.62	0.000	-.0949531	-.0383459
c_age	-.001009	.0010553	-0.96	0.339	-.0030773	.0010593
c_black	.0070798	.0165429	0.43	0.669	-.0253436	.0395032
c_married	.0087691	.0161805	0.54	0.588	-.0229441	.0404823
c_islam	-.0044646	.0188075	-0.24	0.812	-.0413267	.0323974
c_urban	-.0206005	.012957	-1.59	0.112	-.0459957	.0047947
c_maxsent	-.0000705	.0000364	-1.94	0.053	-.0001419	8.90e-07
c_cust_gt3	.0008296	.017385	0.05	0.962	-.0332443	.0349036
c_misAB	-.0056996	.0161849	-0.35	0.725	-.0374214	.0260223
c_hadtc	.000077	.0261838	0.00	0.998	-.0512423	.0513963
c_ever_ac_sol	.0386978	.016362	2.37	0.018	.0066289	.0707667
c_3charge	.0115362	.0129827	0.89	0.374	-.0139094	.0369818
c_p_medlim	.003246	.0145632	0.22	0.824	-.0252973	.0317894
c_p_hsgrad	-.0043757	.012474	-0.35	0.726	-.0288243	.0200729
c_p_had_job	.0007842	.0116143	0.07	0.946	-.0219793	.0235477
c_p_prob_drugalc	.0202249	.0243244	0.83	0.406	-.0274501	.0679
c_p_prob_mh	-.000755	.0099771	-0.08	0.940	-.0203099	.0187998
c_p_usvet	-.0017082	.0234978	-0.07	0.942	-.0477631	.0443467
c_p_iq	-.0003276	.0004217	-0.78	0.437	-.0011541	.0004989
c_18under_1arr	.0059163	.015249	0.39	0.698	-.0239711	.0358037
c_apv	-.0029043	.0209732	-0.14	0.890	-.044011	.0382023
cp_age	-.0030652	.0016535	-1.85	0.064	-.0063059	.0001756

```
        cp_black |  -.0230063   .0266228    -0.86   0.388     -.075186    .0291734
      cp_married |   .0043164   .0355903     0.12   0.903    -.0654393    .0740722
        cp_islam |   .0205401   .0323779     0.63   0.526    -.0429194    .0839995
        cp_urban |  -.0342143   .0244563    -1.40   0.162    -.0821476    .0137191
      cp_maxsent |  -.0000473   .0000787    -0.60   0.548    -.0002014    .0001069
     cp_pri_narr |    .001568   .0030991     0.51   0.613    -.0045062    .0076422
     cp_cust_gt3 |   .0439232    .027654     1.59   0.112    -.0102777     .098124
        cp_misAB |  -.0255816    .036497    -0.70   0.483    -.0971145    .0459512
        cp_hadtc |  -.0097168   .0710757    -0.14   0.891    -.1490225     .129589
    cp_hasPriorI |   .0135357   .0365037     0.37   0.711    -.0580103    .0850816
  cp_ever_ac_sol |   .0420698   .0367979     1.14   0.253    -.0300527    .1141923
      cp_3charge |   .0192885   .0230366     0.84   0.402    -.0258624    .0644394
         cp_rsth |   .0242539   .0164719     1.47   0.141    -.0080305    .0565382
     cp_p_medlim |  -.0059291   .0320513    -0.18   0.853    -.0687485    .0568903
     cp_p_hsgrad |  -.0262224   .0286986    -0.91   0.361    -.0824706    .0300258
    cp_p_had_job |   .0050219   .0227494     0.22   0.825    -.0395661      .04961
cp_p_prob_drugalc |  -.0366481   .0411061    -0.89   0.373    -.1172147    .0439184
    cp_p_prob_mh |  -.0256594   .0245203    -1.05   0.295    -.0737183    .0223996
      cp_p_usvet |  -.0201867   .0474858    -0.43   0.671    -.1132572    .0728838
         cp_p_iq |  -.0001706   .0007879    -0.22   0.829    -.0017148    .0013737
 cp_18under_1arr |  -.0462138   .0358646    -1.29   0.198     -.116507    .0240795
          cp_apv |  -.0227991   .0388972    -0.59   0.558    -.0990361     .053438
       stretches |  -.0086822   .0096214    -0.90   0.367    -.0275398    .0101754
      r_time2rel |   .0000245   .0000267     0.92   0.359    -.0000278    .0000769
      r_staytime |   -.000144   .0000335    -4.30   0.000    -.0002096   -.0000785
     tier_tt_fa |   .0003604    .010948     0.03   0.974    -.0210973    .0218181
               k |   .0729725   .0248391     2.94   0.003     .0242888    .1216563
           _cons |   .6910948   .1440772     4.80   0.000     .4087087    .9734809
-----------------+----------------------------------------------------------------
Mills            |
       rho1-rho0 |  -.0986655   .0367373    -2.69   0.007    -.1706693   -.0266617
-----------------+----------------------------------------------------------------
ATE              |
      E(Y1-Y0)@X |  -.0010905   .0332066    -0.03   0.974    -.0661742    .0639933
----------------------------------------------------------------------------------
(note: file mte_base_t180_has_post0.gph not found)
(file mte_base_t180_has_post0.gph saved)
(running parametric_polynomial on estimation sample)
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Chapter 10 Appendix

Cross-tabulations of the relative risk score versus the fourth, seventh, and tenth deciles of the propensity scores at the 150-day threshold.

rel_pri_narr	p_150_4 0	1	Total
-45	1	0	1
-41	1	0	1
-39	1	0	1
-38	1	0	1
-37	1	0	1
-33	1	0	1
-29	3	0	3
-27	2	0	2
-26	2	0	2
-25	3	0	3
-24	7	0	7
-23	2	0	2
-22	5	0	5
-21	10	1	11
-20	9	1	10
-19	9	1	10
-18	10	3	13
-17	14	2	16
-16	25	1	26
-15	25	2	27
-14	28	3	31
-13	44	4	48
-12	47	9	56
-11	45	13	58
-10	85	7	92
-9	117	13	130
-8	155	14	169
-7	190	21	211
-6	258	35	293
-5	336	33	369
-4	425	42	467
-3	553	60	613
-2	633	86	719
-1	718	83	801
0	909	97	1,006
1	767	86	853
2	672	70	742
3	530	66	596
4	471	49	520
5	352	32	384
6	298	26	324
7	219	36	255
8	208	23	231
9	166	20	186
10	129	11	140
11	101	13	114
12	90	8	98
13	70	6	76
14	58	6	64
15	46	2	48
16	40	6	46
17	35	4	39
18	22	7	29
19	21	6	27
20	26	1	27
21	16	1	17
22	16	3	19
23	11	1	12

24	7	3	10
25	5	1	6
26	7	3	10
27	9	2	11
28	0	2	2
29	1	0	1
30	2	0	2
31	2	0	2
32	3	2	5
33	2	0	2
34	3	0	3
35	2	0	2
36	3	0	3
37	2	1	3
38	1	0	1
39	1	0	1
40	0	3	3
41	2	0	2
42	2	0	2
43	2	0	2
46	3	0	3
63	1	0	1
71	1	0	1
Total	9,100	1,031	10,131

rel_pri_na rr	p_150_7 0	1	Total
-45	1	0	1
-41	0	1	1
-39	1	0	1
-38	1	0	1
-37	1	0	1
-33	0	1	1
-29	1	2	3
-27	2	0	2
-26	2	0	2
-25	3	0	3
-24	6	1	7
-23	2	0	2
-22	5	0	5
-21	10	1	11
-20	7	3	10
-19	10	0	10
-18	13	0	13
-17	16	0	16
-16	22	4	26
-15	24	3	27
-14	27	4	31
-13	44	4	48
-12	53	3	56
-11	54	4	58
-10	82	10	92
-9	116	14	130
-8	157	12	169
-7	193	18	211
-6	264	29	293
-5	336	33	369
-4	415	52	467
-3	561	52	613
-2	670	49	719
-1	731	70	801
0	931	75	1,006
1	786	67	853
2	676	66	742
3	538	58	596

4	462	58	520
5	351	33	384
6	291	33	324
7	229	26	255
8	216	15	231
9	171	15	186
10	132	8	140
11	106	8	114
12	97	1	98
13	71	5	76
14	60	4	64
15	43	5	48
16	43	3	46
17	34	5	39
18	28	1	29
19	26	1	27
20	25	2	27
21	12	5	17
22	16	3	19
23	12	0	12
24	10	0	10
25	5	1	6
26	10	0	10
27	11	0	11
28	2	0	2
29	1	0	1
30	2	0	2
31	1	1	2
32	5	0	5
33	2	0	2
34	2	1	3
35	1	1	2
36	2	1	3
37	3	0	3
38	1	0	1
39	1	0	1
40	3	0	3
41	2	0	2
42	1	1	2
43	2	0	2
46	2	1	3
63	1	0	1
71	1	0	1
Total	9,257	874	10,131

rel_pri_na rr	p_150_10 0	1	Total
-45	1	0	1
-41	1	0	1
-39	1	0	1
-38	1	0	1
-37	1	0	1
-33	1	0	1
-29	3	0	3
-27	1	1	2
-26	1	1	2
-25	2	1	3
-24	6	1	7
-23	2	0	2
-22	4	1	5
-21	8	3	11
-20	10	0	10
-19	9	1	10
-18	9	4	13
-17	15	1	16

-16	21	5	26
-15	24	3	27
-14	29	2	31
-13	44	4	48
-12	48	8	56
-11	54	4	58
-10	80	12	92
-9	117	13	130
-8	146	23	169
-7	179	32	211
-6	265	28	293
-5	319	50	369
-4	399	68	467
-3	525	88	613
-2	625	94	719
-1	694	107	801
0	881	125	1,006
1	736	117	853
2	654	88	742
3	530	66	596
4	442	78	520
5	330	54	384
6	279	45	324
7	231	24	255
8	203	28	231
9	167	19	186
10	117	23	140
11	99	15	114
12	76	22	98
13	63	13	76
14	58	6	64
15	42	6	48
16	37	9	46
17	36	3	39
18	23	6	29
19	22	5	27
20	22	5	27
21	17	0	17
22	17	2	19
23	12	0	12
24	10	0	10
25	5	1	6
26	8	2	10
27	9	2	11
28	2	0	2
29	1	0	1
30	2	0	2
31	2	0	2
32	5	0	5
33	2	0	2
34	3	0	3
35	2	0	2
36	3	0	3
37	3	0	3
38	1	0	1
39	1	0	1
40	3	0	3
41	2	0	2
42	2	0	2
43	1	1	2
46	1	2	3
63	1	0	1
71	1	0	1
Total	8,809	1,322	10,131

Cross-tabulations of the relative risk score versus the fourth, seventh, and tenth deciles of the propensity scores at the 150-day threshold.

rel_rsth	p_150_4 0	1	Total
-7	2	0	2
-6	8	2	10
-5	48	3	51
-4	169	22	191
-3	480	52	532
-2	946	107	1,053
-1	1,454	142	1,596
0	1,900	205	2,105
1	1,763	198	1,961
2	1,176	139	1,315
3	724	108	832
4	309	37	346
5	104	16	120
6	16	0	16
7	1	0	1
Total	9,100	1,031	10,131

rel_rsth	p_150_7 0	1	Total
-7	1	1	2
-6	9	1	10
-5	44	7	51
-4	181	10	191
-3	493	39	532
-2	953	100	1,053
-1	1,455	141	1,596
0	1,916	189	2,105
1	1,795	166	1,961
2	1,209	106	1,315
3	760	72	832
4	313	33	346
5	112	8	120
6	15	1	16
7	1	0	1
Total	9,257	874	10,131

rel_rsth	p_150_10 0	1	Total
-7	1	1	2
-6	9	1	10
-5	42	9	51
-4	167	24	191
-3	462	70	532
-2	903	150	1,053
-1	1,353	243	1,596
0	1,811	294	2,105
1	1,722	239	1,961
2	1,170	145	1,315
3	734	98	832
4	313	33	346
5	108	12	120
6	14	2	16
7	0	1	1
Total	8,809	1,322	10,131

Rearrest offenses for releasees: drug crimes.

offlit	Freq.	Percent	Cum.
ACQ OR OBT POSS OF CONTR SUBS MISRE	32	0.37	0.37
ADMIN ETC OF CONT SUBST BY PRACT	4	0.05	0.41
ADULT/MUTI/DEST LABEL	4	0.05	0.46
ADULTE MISBRAND ANY CONTROLLED SUBST	5	0.06	0.52
COUNTER SIMULAT MARK STAMP	3	0.03	0.55
DELIVER/INTENT TO DEL DRUG PARA	18	0.21	0.76
DISSEM/PUB OF FALSE/MISLEAD ADV	1	0.01	0.77
INT POSS CONTR SUBST BY PER NOT REG	3,360	38.71	39.48
KNOWING/IN MFTR/DIST OF DESIGN DRUG	2	0.02	39.50
MANUF ETC CONTROLLED SUBSTANCE	9	0.10	39.60
MANUF/DEL/POSS/W INT MANUF OR DEL	2,143	24.69	64.29
MISBRANDING / DETERIORATION	1	0.01	64.30
OPERATING A METHAMPHETAMINE LAB	7	0.08	64.38
POSS OF MARIJUANA	1,059	12.20	76.58
POSS W/INT TO DISTR NC SUBS RES CONTR	28	0.32	76.90
POSSESS RED PHOS, ETC W/ INTENT TO MA..	1	0.01	76.92
PROCURE FOR SELF/OTHER DRUG BY CONC M..	5	0.06	76.97
PURC/REC OF CONT SUBSTBY UNAUTH PER	180	2.07	79.05
SALE GIVE CONTR SUBS TO DEP PERSON	15	0.17	79.22
SALE OF CONTROLLED SUBSTANCE	6	0.07	79.29
SALE RETAIL OF DRUG EXCEPT PHARMACIST	2	0.02	79.31
SELL ETC CONTR SUBST W/KNOW TM	1	0.01	79.32
USE/POSS OF DRUG PARAPH	1,795	20.68	100.00
Total	8,681	100.00	

Rearrest offenses for releasees: violent crimes.

offlit	Freq.	Percent	Cum.
ACC INVOLVING DEATH/INJURY-NOT PROPER..	4	0.05	0.05
ACCIDENT INV DEATH-ATTEM	6	0.07	0.12
ACCIDENTS INVOLV.DEATH/PERSONAL INJURY	24	0.29	0.41
AGG ASSAULT WHILE DUI	5	0.06	0.47
AGG INDECENT ASST-SOLIC	15	0.18	0.64
AGG. ASSAULT OF UNBORN CHILD	6	0.07	0.72
AGG. IND. ASSAULT - COMP. LESS THAN 1..	3	0.04	0.75
AGG. IND. ASSAULT - COMP. LESS THAN 16	4	0.05	0.80
AGG. IND. ASSAULT - FORCIBLE COMPULSION	5	0.06	0.86
AGG. IND. ASSAULT - THREAT OF FORCIBL..	3	0.04	0.89
AGG. IND. ASSAULT OF CHILD	2	0.02	0.92
AGG. IND. ASSAULT W/O CONSENT	24	0.29	1.20
AGGRAV INDEC ASSLT-W/O CONS	6	0.07	1.28
AGGRAVATED ASSAULT	1,027	12.25	13.52
AGGRAVATED ASSAULT OF UNBORN CHILD	2	0.02	13.55
AGGRAVATED HARASSMENT BY PRISONER	17	0.20	13.75
ASSAULT BY PRISONER	17	0.20	13.95
ATTEMPTED KIDNAPPING	11	0.13	14.08
ATTEMPTED SEXUAL ASSAULT	55	0.66	14.74
CONCEAL WHEREABOUTS OF CHILD	3	0.04	14.78
CONCEALMENT OF WHEREABOUTS OF A CHILD	1	0.01	14.79
CRIMINAL HOMICIDE	47	0.56	15.35
DISCHARGE OF FIREARM	17	0.20	15.55
ETHNIC INTIMIDATE	3	0.04	15.59
FALSE IMPRISONMENT	92	1.10	16.68
FALSE IMPRISONMENT-ATTEM	51	0.61	17.29
FIRST DEGREE MURDER OF UNBORN CHILD	1	0.01	17.30
HARASSMENT	155	1.85	19.15

HARASSMENT - COMM. LEWD, THREATENING,..	113	1.35	20.50
HARASSMENT - COMM. REPEATEDLY IN ANON..	16	0.19	20.69
HARASSMENT - COMM. REPEATEDLY IN ANOT..	17	0.20	20.89
HARASSMENT - FOLLOW IN PUBLIC PLACE	10	0.12	21.01
HARASSMENT - SUBJECT OTHER TO PHYSICA..	547	6.52	27.54
HARASSMENT-PHYSICALLY STRIKE KICK ETC	37	0.44	27.98
HOMI BY VEH WHILE DR UNDER THE INFL	1	0.01	27.99
HOMICIDE	17	0.20	28.19
HOMICIDE BY VEHICLE	5	0.06	28.25
HOMICIDE BY VEHICLE/ DRIV UNDER INFLU..	1	0.01	28.26
IDSI FORCIBLE COMPULSION	34	0.41	28.67
IDSI PERSON LESS THAN 13 YRS AGE	4	0.05	28.72
IDSI PERSON LESS THAN 16 YRS AGE	11	0.13	28.85
IDSI PERSON UNCONSCIOUS	2	0.02	28.87
IDSI THREAT FORCIBLE COMPULSION	6	0.07	28.94
IND ASSAULT VICTIM MENT DEF	1	0.01	28.96
IND ASSLT PERSON LESS 13 YRS AGE	35	0.42	29.37
IND ASSLT PERSON LESS 16 YRS AGE	21	0.25	29.62
INDEC ASSL-CUST OF LAW/HOSP	1	0.01	29.64
INDEC ASSL-SUBST'L IMPAIR	8	0.10	29.73
INDEC ASSLT-MENTAL DISEASE/DEFECT	27	0.32	30.05
INDEC ASSLT-OTHER UNAWARE	8	0.10	30.15
INDEC ASSLT-W/O CONS OF OTHER	72	0.86	31.01
INDECENT ASSAULT-CONSP	18	0.21	31.22
INDECENT EXPOSURE	50	0.60	31.82
INDECENT EXPOSURE-CONSP	24	0.29	32.10
INTERFERENCE W/CHILD-CC	5	0.06	32.16
INTERFERENCE W/CUSTODY OF CHILDREN	14	0.17	32.33
INVOL. DEVIATE SEXUAL INTERCOURSE W/C..	3	0.04	32.37
INVOLUNTARY MANSLAUGHTER	5	0.06	32.43
KIDNAP TO FACILITATE A FELONY	8	0.10	32.52
KIDNAP TO INFLICT INJ/TERROR	8	0.10	32.62
KIDNAPPING FOR RANSOM	16	0.19	32.81
KIDNAPPING-INTERFERE W/PUBLIC OFFICIAL	1	0.01	32.82
LURE CHILD INTO MOTOR VEHICLE	7	0.08	32.90
LURE CHILD INTO VEH-ATT	2	0.02	32.93
MURDER OF THE FIRST DEGREE	45	0.54	33.46
MURDER OF THE SECOND DEGREE	7	0.08	33.55
MURDER OF THE THIRD DEGREE	23	0.27	33.82
MURDER-CONSPIRACY	99	1.18	35.00
PROPEL MISSILE INTO OCC VEHICLES	7	0.08	35.09
PROPELLING MISSILES INTO OCCUPIED VEH..	4	0.05	35.13
RAPE FORCIBLE COMPULSION	10	0.12	35.25
RAPE OF CHILD	10	0.12	35.37
RAPE PERSON LESS THAN 13 YEARS OLD	1	0.01	35.38
RAPE SUBSTANTIALLY IMPAIRED PERSON	2	0.02	35.41
RAPE THREAT OF FORCIBLE COMPULSION	12	0.14	35.55
RAPE UNCONSCIOUS VICTIM	5	0.06	35.61
RAPE-CONSPIRACY	18	0.21	35.83
RAPE-STATUTORY	2	0.02	35.85
REAP	1,535	18.31	54.16
SIMPLE ASSAULT	2,152	25.66	79.82
SIMPLE ASSAULT - MUTUAL CONSENT FIGHT	10	0.12	79.94
SIMPLE ASSAULT-CONSP	364	4.34	84.28
SODOMY	12	0.14	84.42
STALKING	1	0.01	84.44
STALKING - REPEATEDLY COMMIT ACTS TO ..	56	0.67	85.10
STALKING-SOLICIT	68	0.81	85.92
STATUTORY SEX ASST-CONSP	36	0.43	86.34
TERRORISTIC THREATS CAUSE EVACUATION ..	3	0.04	86.38
TERRORISTIC THREATS CAUSE SERIOUS PUB..	11	0.13	86.51
TERRORISTIC THREATS W/ INT TO TERRORI..	555	6.62	93.13
TERRORISTIC THREATS-SOL	379	4.52	97.65
UNLAW RESTRAINT/INVOL SERVITUDE	3	0.04	97.69
UNLAW RESTRAINT/RISK SER INJURY	10	0.12	97.81
UNLAWFUL RESTRAINT-CONSP	177	2.11	99.92
UNLAWFUL RESTRAINT/ SERIOUS BODILY IN..	2	0.02	99.94
VOL.MANSLAUGHTER UNBORN CHILD/MOTHER ..	1	0.01	99.95
VOLUNTARY MANS - PROVOCATION FROM IND..	2	0.02	99.98

VOLUNTARY MANS - UNREASONABLE BELIEF	1	0.01	99.99
WEAPON OF MASS DESTRUCTION	1	0.01	100.00
Total	8,385	100.00	

Rearrest offenses for releasees: property crimes.

offlit	Freq.	Percent	Cum.
AGRICULTURAL VANDALISM	2	0.02	0.02
ARSON - PERSON PROP EXC $5000	5	0.06	0.08
ARSON - RECKLESS PLACE PERSONS DANGER	5	0.06	0.13
ARSON AND DANGER OF DEATH OR BODILY I..	10	0.11	0.24
ARSON ENDANGERING PROPERTY	5	0.06	0.30
ARSON, ENDANGERING PROPERTY	1	0.01	0.31
ATT THEFT BY EXTORTION LEGAL HARM	1	0.01	0.32
ATTEMPTED BURGLARY	133	1.48	1.80
BAD CHECKS	85	0.94	2.74
BURGLARY	661	7.33	10.07
BURGLARY-BLDG W/O OVERNIGHT ACCOM.	12	0.13	10.21
BURGLARY-FROM ANY TYPE VEHICLE	184	2.04	12.25
CAUSING CATASTROPHE	6	0.07	12.31
CAUSING/RISKING CATASTROPHE	11	0.12	12.44
COPYING; DEVICES	3	0.03	12.47
CREDIT CARD USED TO OBT OR ATT OBT PR..	55	0.61	13.08
CREDIT CARDS	1	0.01	13.09
CRIM MISCH/DMG PROP INTENT, RECKLESS,..	123	1.36	14.46
CRIM'L MISCH-ANOTHER PECUN LOSS	4	0.04	14.50
CRIM'L MISCH-TAMPER W/PROPERTY	112	1.24	15.74
CRIMINAL MISCHIEF	369	4.09	19.84
CRIMINAL MISCHIEF - DAMAGE PROPERTY -..	207	2.30	22.13
CRIMINAL TRESPASS	12	0.13	22.27
DEC BUS PRACT - FALSE/MIS STATE CRED	1	0.01	22.28
DEC BUS PRACT - SALE LESS THAN QUANT	4	0.04	22.32
DECEPTIVE PRACTICES-ATT	3	0.03	22.35
FAIL TO FURN INFO/RET FALSE INFOR	1	0.01	22.37
FALSE STMT TO INDUCE AGENT FOR HOME I..	1	0.01	22.38
FALSE/FRAUD/INCOMP INSURANCE CLAIM	4	0.04	22.42
FALSELY IMPERSONATING PERSONS PRIVATE..	1	0.01	22.43
FORGERY - ALTER WRITING	61	0.68	23.11
FORGERY - UTTERS FORGED WRITING	58	0.64	23.75
FORGERY-SOLICITATION	21	0.23	23.98
FORGERY-UNAUTHORIZED ACT IN WRITING	111	1.23	25.22
FRAUD ALTER/FORG/COUNTER TITLE REG INS	14	0.16	25.37
FRAUD OBT FOODSTAMPS/ASSISTANCE	1	0.01	25.38
FRAUDULENT CERTIF OF TITLE-STOLEN VEH..	3	0.03	25.42
FRAUDULENT USE OF CREDIT CARD UNDER 5..	21	0.23	25.65
IDENTIFY THEFT - CONSP	19	0.21	25.86
IDENTITY THEFT	63	0.70	26.56
ILLEGAL SALES	1	0.01	26.57
INJURING OR TAMPERING WITH FIRE APPAR..	3	0.03	26.60
INSTIT VANDALISM-ATTEMPT	5	0.06	26.66
INSTITUT'L VAND'ISM EDUC FACIL	9	0.10	26.76
INSURANCE FRAUD	1	0.01	26.77
LARCENY BY EMPLOYEE	147	1.63	28.40
LIBRARY THEFT-SOLICIT	2	0.02	28.42
MAKE CHECK W/O FUNDS	18	0.20	28.62
MAKE FALSE APPLI FOR TITLE REG	3	0.03	28.66
OBTAIN PROPERTY OR CREDIT BY FALSE ST..	37	0.41	29.07
OWNING, OPERATING OR CONDUCTING A CHO..	5	0.06	29.12
POSS SOLV FOR RELEAS TOXIC VAPORS/FUMES	1	0.01	29.13
POSSES ACCESS DEVICE KNOWING COUNTERF..	18	0.20	29.33
POSSESS EXPLOSIVE/INCEN MATERIAL	1	0.01	29.34
PUBL, MAKE, SELL, ETC CREDIT CARD ALT..	8	0.09	29.43
RECEIVING STOLEN PROPERTY	1,625	18.03	47.46
RETAIL RECORDED DEVICE	4	0.04	47.50

RETAIL THEFT	5	0.06	47.56
RETAIL THEFT - TAKE MDSE	829	9.20	56.76
RETAIL THEFT - TRANS MDSE FR CONT	9	0.10	56.86
RETAIL THEFT-ALTER LABEL/PRICE MARKING	10	0.11	56.97
RETAIL THEFT-UNDER-RING	4	0.04	57.01
RISKING CATASTROPHE	8	0.09	57.10
ROBBERY	147	1.63	58.73
ROBBERY (PHYSICALLY TAKES OR REMOVES ..	9	0.10	58.83
ROBBERY (THREATENS OR INFLICTS BODILY..	3	0.03	58.86
ROBBERY OF MOTOR VEHICLE	26	0.29	59.15
ROBBERY-CONSPIRACY	210	2.33	61.48
ROBBERY-INFLICT SERIOUS BODILY INJURY	116	1.29	62.77
SECURING EXEC DOCUMENTS BY DECEPTION	32	0.36	63.12
SIMULATING OBJ OF ANTIQUITY,RARITY,ETC	3	0.03	63.16
SMELL/INHALE TOXIC RELEASING SUBSTANCES	1	0.01	63.17
TAMPER RECORDS OR ID-WRITING	24	0.27	63.43
THEFT BY DECEP-FALSE IMPRESSION	204	2.26	65.70
THEFT BY DECEPT-PREVENT ACQU OF INFO	18	0.20	65.90
THEFT BY DECEPTION	4	0.04	65.94
THEFT BY DECEPTION-FAIL TO CORRECT	17	0.19	66.13
THEFT BY FAIL TO MAKE REQ DISP FUNDS	7	0.08	66.21
THEFT BY RECEIVING STOLEN PROPERTY	357	3.96	70.17
THEFT BY UNLAW TAKING-IMMOVABLE PROP	12	0.13	70.30
THEFT BY UNLAW TAKING-MOVABLE PROP	1,534	17.02	87.32
THEFT FROM A MOTOR VEHICLE	5	0.06	87.38
THEFT OF LEASED PROPERTY	9	0.10	87.48
THEFT OF LOST PROPERTY	18	0.20	87.67
THEFT OF MOTOR VEHICLE	61	0.68	88.35
THEFT OF SERVICES	2	0.02	88.37
THEFT OF SERVICES-ACQUIS OF SERVICE	6	0.07	88.44
THEFT OF SERVICES-ACQUISITION OF SERV..	3	0.03	88.47
THEFT-FAIL TO MAKE-CONSP	1	0.01	88.48
THEFT-UNLWF TAKING-ATTEM	334	3.71	92.19
TRADEMARK COUNTERFEITING	22	0.24	92.43
TRESPASS, CRIMINAL	178	1.97	94.41
TRESPASS, DEFIANT (NOTICE AGAINST TRE..	54	0.60	95.01
UNAUTH USE MOTOR/OTHER VEHICLES	244	2.71	97.71
UNLAWFUL ENTRY	199	2.21	99.92
UNLAWFUL POSS. RETAIL/LIBRARY THEFT I..	1	0.01	99.93
UNLAWFUL USE OF COMPUTER-DESTROY DATA	1	0.01	99.94
VIOL USE LIMITED ACCESS HWY	1	0.01	99.96
VIOLATE ARTICLE	1	0.01	99.97
VIOLATION OF GAMBLING LAWS	2	0.02	99.99
VIOLATION OF PUBLIC WELFARE CODE	1	0.01	100.00
Total	9,014	100.00	

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