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Labor Force Participation and Crime among Serious and Violent Former Prisoners

by
Nora Ellen Wikoff

A dissertation presented to the
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List of Abbreviations

AIC	Aikaike Information Criterion
AFQT	Armed Forces Qualifying Test
B	Unstandardized Coefficient
BIC	Bayesian Information Criterion
CEO	Center for Employment Opportunities
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CI	Confidence Interval
DM	Duration Models
DF	Degrees of freedom
FBI	Federal Bureau of Investigation
FIML	Full-Information Maximum Likelihood
GED	General Education Development (General Equivalency Diploma)
GSI	Global Severity Index
GTM	Group-Based Trajectory Model
HR	Hazard Ratio
HSD	High School Diploma
LSEM	Longitudinal Structural Equation Model
ML	Maximum Likelihood
M	Mean
MH/AOD	Mental Health, Alcohol, or Drug
NCIC	National Crime Information Center
OR	Odds Ratio
PSM	Propensity Score Methods
RMSEA	Root Mean Square Error of Approximation
RNR	Risk-Need-Responsivity
SD	Standard Deviation
SE	Standard Errors
SEM	Structural Equation Modeling
SR	Self-Report
SVORI	Serious and Violent Offender Reentry Initiative
TABE	Tests of Adult Basic Education
TANF	Temporary Assistance to Needy Families
TLI/NNFI	Tucker-Lewis Index (Non-Normed Fit Index)

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Nora Wikoff

Washington University in St. Louis

May 2015

Dedicated to my husband.

ABSTRACT OF THE DISSERTATION

Labor Force Participation among Serious and Violent Former Prisoners

by

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Doctor of Philosophy in Social Work

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Professor Carrie Pettus-Davis, Co-Chair

Professor Michael Sherraden, Co-Chair

This project examines the relationship between work and crime among male former prisoners. Criminological theories and observational studies suggest that work reduces crime, but recent studies cast doubt on the ability of employment programs to reduce recidivism among former prisoners. Ongoing weak evaluations may imperil support for employment-focused rehabilitative programming. Using data from the Serious and Violent Offender Reentry Initiative (*n* = 1,575), this study examines whether selection bias and unobserved heterogeneity contribute to weak evaluation findings.

First, this study tests whether unobserved heterogeneity contributes to jobs programs' weak treatment effects. It uses group-based trajectory modeling and propensity score methods to balance participants and nonparticipants on demographic and criminal risk factors. Lifetime arrest data from administrative records are used to model respondents' prior offending trajectories. Baseline interview data are used to balance respondents on the propensity to receive employment-focused services. After balancing respondents, this study employs duration models to test the effects of educational and employment programming on time to rearrest.

Second, this study tests whether financial problems mediate the work-crime relationship. Longitudinal structural equation modeling is used to model men's labor force attachment, job quality, financial needs, and emotional wellbeing. Models test whether financial problems diminish the crime-reducing effects of employment for men who remain weakly attached to the labor force. Multiple indicators for each latent construct reduce bias due to measurement error.

Results of this study show that education and employment programs in United States prisons have limited effects on the likelihood that participants maintain employment and avoid criminal justice involvement. Male prisoners recruited into the Serious and Violent Offender Reentry Initiative faced multiple barriers to employment before entering prison, due to extensive criminal records, low educational attainment, and limited work experience. Before matching men on the probability of receiving employment-focused services, program participants differed from nonparticipants across an array of demographic and risk factors. The group-based trajectory model derived three latent trajectory groups from the sample that exhibited distinctive demographic characteristics and pre-prison offending trajectories. Due to significant variation at the state-level, a multilevel logit model was used to model the probability of receiving education and employment services. Nearest neighbor matching with caliper resulted in a sample that exhibited balance across multiple demographic, criminal record, employment, and health measures.

After matching, employment program participants were slightly more likely than education participants and nonparticipants to maintain stable employment, and employment program participants exhibited lower rates of rearrest during the first 9 months after release. After that point, there were no significant differences between employment-focused program participants and nonparticipants in labor force and criminal activity.

The longitudinal structural equation model results show that criminal activity has cascading effects on financial and emotional wellbeing, subsequent labor force activity, and ongoing criminal justice involvement. Engagement in crime during the early months of release reduced labor force participation, limited men's ability to obtain higher-quality employment, and increased their financial needs and feelings of psychological distress. In contrast, stable employment led to improved job quality and reduced financial needs over time. Employment did not reduce men's later involvement in criminal activity, however. In fact, employment during the first 9 months of release was associated with increased odds of reporting committing new crimes during the subsequent 6-month period. Overall, the path model results provide no evidence to suggest that stable employment reduces criminal activity among serious and violent former prisoners.

The results of this study cast doubt on theories of crime that presuppose causal associations between work and crime. Observational studies that show associations between stable labor force participation and desistance from crime may be capturing maturation effects that simultaneously directed individuals toward legal work and away from crime. If desistance from crime actually precedes stable labor force attachment for most former prisoners, this may explain the weak empirical evidence for prison-based employment programs. The findings may inform modifications to employment and transitional jobs programs to identify participants on the path to desistance who may be most responsive to these services.

Chapter 1: Specific Aims

This study examines the relationship between work and crime among newly released former prisoners. Criminological theories propose various mechanisms by which work reduces crime: It limits opportunities for deviant behavior, strengthens prosocial attachments, and reduces financial incentives to engage in crime (Grogger, 1998; Hirschi, 1969; Latessa, 2012). Observational studies provide empirical support for these claims, suggesting that even among active offenders, work has a weak causal effect on crime (Bushway, 2011). This lends credence to employment-focused prison programs: If work reduces crime, then increasing employment among reentering former prisoners should reduce recidivism. Unfortunately, jobs programs show limited success in helping many prisoners gain job skills, find and maintain work, and reduce their involvement in crime (Bushway & Apel, 2012; Farabee, Zhang, & Wright, 2014; Lattimore et al., 2012; J. A. Wilson & Davis, 2006).

Strengthening our understanding of the relationship between work and crime is critical to designing effective employment programs for low-skilled, low-educated former prisoners with limited formal work experience. Interventions may not reduce recidivism rates if work, although correlated, is not causally related to reduced crime among former prisoners (Farabee et al., 2014; Grogger, 1998; D. B. Wilson, Gallagher, & MacKenzie, 2000). Employment may reduce individuals' incentives to engage in economically motivated crimes, but it may have limited effects on other crimes (Aaltonen, Macdonald, Martikainen, & Kivivuori, 2013; Felson, Osgood, Horney, & Wiernik, 2012). Former prisoners who find work may continue to engage in criminal activity (Horney, Osgood, & Marshall, 1995), especially when workplace settings provide new opportunities for crime (Lochner, 2004).

This study examines the effects of employment-focused programs on prisoners' post-release labor force participation, job quality, and criminal involvement. Its findings will contribute knowledge to three broad questions at the heart of current scholarship on crime and economics: Does employment have a causal effect on offending among former prisoners? What factors contribute to the relationship between work and crime among former prisoners? What factors explain why employment programs have limited effects on labor activity and recidivism?

I first investigate whether mixed and negative outcomes for employment programs result from selection effects in who receives employment services (Chamberlain, 2012; Heckman & Hotz, 1989; Sedgley, Scott, Williams, & Derrick, 2010). First, if treatment participants have fewer job skills than do people in the comparison group, then post-release outcomes in part reflect pre-existing differences that selected people into treatment (Chamberlain, 2012; Heckman & Hotz, 1989). Second, when prison programs are offered à la carte to prisoners—rather than as bundled sets of programs—the comparison group for employment programs includes both true nonparticipants and people who participated in education programs or prison work. This unmodeled contamination may bias estimates of the intervention under evaluation (Sedgley et al., 2010). After controlling for observed heterogeneity in treatment status, I examine whether participation in educational or employment programs increase men's time in the community (Brewster & Sharp, 2002; Farabee et al., 2014; Kim & Clark, 2013; Sedgley et al., 2010).

Next, I use structural equation modeling (SEM) to study men's labor force and criminal activities during the first 15 months of release from prison. The cross-lagged panel model examines whether crime weakens men's attachment to the labor force (Thornberry & Christenson, 1984). The longitudinal structural equation model (LSEM) includes factors that shape men's incentives to work, to identify whether labor force participation signals men's likelihood of reoffending

(Bushway, 2011; Bushway & Apel, 2012). Finally, I examine whether financial and psychological stressors mediate the relationship between work and crime. The LSEM results provide information about interpersonal and financial challenges that men face following release from prison (Bollen & Brand, 2010; Bucklen & Zajac, 2009; Price, Choi, & Vinokur, 2002).

1.1 State of Current Knowledge

By 2008, 1 in 100 Americans were in jail or prison on any given day. Risk of incarceration is exponentially higher for young, racial and ethnic minority men with less than a high school diploma (Beck et al., 1993; Pew Center on the States, 2008). African Americans and Hispanics compose nearly 60% of prisoners incarcerated in state and federal prisons[1] (Pettit & Western, 2004; Western & Wildeman, 2009). To put this in context, African American men were six times as likely as White men to be imprisoned in state and federal prisons in 2013 (Carson, 2014). African American males are now twice as likely to have been incarcerated as to have bachelor's degrees, and they are more likely to be incarcerated than to be employed (37% vs. 26%) (Western & Wildeman, 2009).

Nearly all of these prisoners are released from prison (95%), but many of them are returned to prison as well (Piehl & Useem, 2011). During their first 3 years of release, more than two-thirds of prisoners are rearrested, nearly half are returned to prison for any reason, and almost one-quarter are imprisoned for a new crime (Durose, Cooper, & Snyder, 2014; Langan & Levin, 2002). Between 1980 and 2006, the proportion of state prisoners admitted for parole violations doubled from 17% to 35% (Sabol & Couture, 2008). By 2013, this percentage had stabilized to 9% of federal prisoners and 28% of state prisoners (Carson, 2014). Parolees are responsible for

[1] Non-Hispanic Whites comprise only 32% of the state and federal prison population (Asians, American Indians and Alaskan Natives, and people of two are more races comprise the remaining 8%).

roughly 20% of the violent and property offenses that lead to arrests (Rosenfeld, Wallman, & Fornango, 2005).

1.1.1 Labor Force Participation Before and After Prison

Appendix A summarizes important studies on post-release employment and crime. Prisoners exhibit significant education and job skills deficits that diminish their job prospects and expected earnings (Lattimore et al., 2012). Minorities face additional barriers to employment, due to racial discrimination, weak local labor markets, and macro-level structural conditions, including recessions and structural unemployment (Bellair & Kowalski, 2011). Time spent out of the labor market while in prison reduces opportunities for men to develop prosocial ties to employment networks (Apel & Sweeten, 2010b; Hagan, 1993). While incarcerated, few men participate in education and job training programs, due to the lack of availability of programming and other systemic issues, so they have limited opportunities to acquire job skills (Chamberlain, 2012; Harlow, 2003; Piehl & Useem, 2011).

Despite this, high rates of joblessness among former prisoners reflect labor force nonparticipation, not just unemployment (Apel & Sweeten, 2010b; Bucklen & Zajac, 2009; Chamberlain, 2012; Sugie, 2014). For most men, the difficulty lies in *keeping* jobs, not in *finding* jobs (Aaltonen et al., 2013; Bucklen & Zajac, 2009; Sugie, 2014; van der Geest, Bijleveld, & Blokland, 2011). Data consistently show that men exhibit short-term boosts in post-release employment and earnings (Apel & Sweeten, 2010b; Nagin & Waldfogel, 1998). Over time, declining external pressures from parole officers and family members to find work, and increasing frustration with low-wage work, leads former prisoners to withdraw from the labor market (Sugie, 2014). Post-release employment and earnings eventually decline to pre-prison levels as men supplement income through illegal activity (Apel & Sweeten, 2010b; Nagin & Waldfogel, 1998; Pettit & Lyons, 2009).

1.1.2 Labor Force Participation and the Desistance Process

The desistance literature presents three competing explanations for observed associations between labor force status and desistance from crime (Giordano, Cernkovich, & Rudolph, 2002; Laub & Sampson, 2001; Massoglia & Uggen, 2010; Skardhamar & Savolainen, 2014). The *turning point hypothesis* makes the strongest case for a causal association between employment and reduced offending. From this perspective, stable employment facilitates the development of social bonds to prosocial institutions and individuals, even among active offenders who may not have expressed any interest in finding work. Reoffending would imperil these social bonds, so employment promotes desistance by providing former prisoners a stake in conformity (Laub & Sampson, 2001).

The *hook-for-change hypothesis* presents a more measured explanation of how employment promotes desistance (Giordano et al., 2002). From this perspective, employment provides the scaffolding needed to help former prisoners carry forth their intentions to go straight, but internal cognitive transformations undergird the desistance process. Obtaining, or receiving, paid employment will have limited effect on subsequent offending among men who have not undergone these cognitive transformations (Bushway, 2003; Giordano et al., 2002; Uggen, 2000).

In contrast to these causal explanations, the *maturational reform hypothesis* states that the spurious association between labor force attachment and desistance from crime reflects internal cognitive transformations that simultaneously shift men toward employment and away from crime. Stable employment does not help former prisoners carry out their intentions to desist from crime; it is the natural result of cognitive changes that led men away from criminal activity in the first place (Skardhamar & Savolainen, 2014).

1.1.3 Interventions to Increase Labor Force Participation

Appendix B summarizes evaluations of employment-focused interventions. The following paragraphs highlight noteworthy findings from these evaluations. Education programs show greater reductions in recidivism than vocational and work programs do, but neither type of program significantly improves labor force outcomes (Brewster & Sharp, 2002; Lattimore et al., 2012; D. B. Wilson et al., 2000). Prison education programs prioritize remedial education and General Education Development (GED) courses over postsecondary courses that would improve prisoners' employability and wages (Brown, 2015; Chamberlain, 2012). Passing the GED test can increase wages among prisoners who fare worst in the labor market, but GED holders' earnings often resemble high school dropouts' earnings more closely than high school graduates' earnings (Apel & Sweeten, 2010b; Heckman & LaFontaine, 2006; Heckman & Rubinstein, 2001; Tyler & Kling, 2007).

Employment readiness programs for prisoners often have limited impacts on post-release employment and recidivism (Bushway, 2003; Farabee et al., 2014; Lattimore et al., 2012). Commonly cited reasons for negative program evaluations include poor program designs, weak program fidelity, and selection bias (manifested by voluntary enrollment and treatment noncompliance) (Farabee et al., 2014; D. B. Wilson et al., 2000). Programs are rarely designed and equipped to provide the comprehensive services needed to improve participants' job prospects (e.g., vocational training, postsecondary education) (Bushway, 2003). Employment programs vary widely in quality, content, and intensity; for example, classes that teach interview skills and provide advice on discussing the criminal record are included in the same category as vocational training (Lattimore et al., 2012).

Selection bias due to voluntary enrollment is commonly assumed to produce upwardly biased treatment estimates (D. B. Wilson et al., 2000). However, selection bias that results from treatment group dropout and comparison group substitution may produce downwardly biased estimates: Mandated programs serve prisoners who have no interest in the topics presented, so the content has limited impact on treatment members' later job searches (Bushway, 2003; Bushway & Apel, 2012). At the same time, the comparison condition for most voluntary and randomized prison interventions permits access to treatment as usual, which often means access to services that are similar to the treatment services being evaluated (Farabee et al., 2014; Heckman, Hohmann, Smith, & Khoo, 2000; Sedgley et al., 2010). In evaluations with high rates of dropout and substitution, observed differences in outcomes between the treatment and comparison groups reveal the effect of the program (e.g., the particular intervention being offered to treatment participants), not the effect of the treatment (e.g., employment services for former prisoners) (Farabee et al., 2014). These attenuated estimates contribute to findings that employment and jobs programs do not work (Heckman et al., 2000).

Program designs, implementation difficulties, and selection bias may have contributed to negative findings for employment programs implemented as part of the Severe and Violent Offender Reentry Initiative (SVORI). This large, multi-site reentry initiative provided states funding to expand existing services for reentering prisoners to be more comprehensive and to begin prior to release into the community. Although SVORI programs increased the number of services that participants received, the programs did not appear to increase employment or reduce recidivism (Lattimore et al., 2012; Lattimore & Steffey, 2009). Most men received no education or employment assistance in prison, despite high rates of men indicating that they needed help with education and employment (Lattimore & Steffey, 2009; Lattimore, Steffey, & Visher, 2009).

SVORI employment programs varied widely in terms of content, intensity, and duration (Lattimore & Steffey, 2009; D. B. Wilson et al., 2000), but limited data on services and participation kept evaluators from differentiating programs by quality (Lattimore et al., 2012). Employment program nonparticipants likely worked in prison or received education assistance in place of employment services (Chamberlain, 2012; Lattimore et al., 2012; Lattimore et al., 2009). To the extent that education programs improve prisoners' human capital and soft skills, educational programs provide a competing treatment to employment programs. When employment program nonparticipants within the comparison group opt for educational services (in place of no treatment), this unobserved participation in comparable services contaminates the sample, often reducing the observed effect of employment programs on work and recidivism outcomes (Bushway & Apel, 2012; Lattimore et al., 2012; Sedgley et al., 2010).

Initial evaluations suggested that SVORI participants exhibited slightly better employment outcomes than non-SVORI participants, regardless of participation in education or employment programs: In general, SVORI participants received more services than did non-SVORI participants, so these short-term effects may have reflected the cumulative benefit of receiving bundled services that addressed an array of needs. At each post-release interview, SVORI participants were more likely to hold jobs with benefits than non-SVORI participants were. By the final 15-month follow-up interview, SVORI participation increased men's probability of supporting themselves through employment. Despite these beneficial outcomes, SVORI participation did not increase the average number of months that men worked between interview reference periods (two-thirds of months), and SVORI participants were no more likely than non-SVORI participants to maintain employment throughout each of the 3- to 6-month interview reference periods (Lattimore et al., 2009).

Subtle improvements in SVORI participants' labor force outcomes did not translate into reduced rearrest and reincarceration (i.e., recidivism) during men's first 24 months following release. SVORI and non-SVORI participants showed equivalent rates of recidivism during each post-release quarter (Lattimore et al., 2009). Multiple logistic regression models that included men's SVORI status and indicators for participation in education, employment, and other reentry services provide limited support for education programs, and almost no support for employment services. Education programs were weakly associated with improved labor outcomes over the follow-up waves, but they did not significantly reduce men's odds of rearrest or reincarceration. Conversely, employment services were not associated with post-release employment status or job quality but were associated with shortened time to first rearrest (Lattimore et al., 2012).

1.2 Gaps in Existing Research

Employment and education programs implicitly, if not explicitly, assume that jobs function as crime-prevention levers for former prisoners (Bushway & Apel, 2012; Farabee et al., 2014; Redcross, Millenky, Rudd, & Levshin, 2012). By increasing participants' job skills, these services should increase labor force activity and reduce offending (Bushway, 2003). Research is needed to confirm that associations between post-release work and desistance do not simply reflect an underlying common cause (e.g., maturational reform) (Maruna, 2001; Skardhamar & Savolainen, 2014). Prisoners who maintain employment may differ systematically from persistently unemployed prisoners in ways that contribute to observed differences in recidivism (Flinn & Heckman, 1983). Most observational studies that suggest employment reduces recidivism among former prisoners provide correlational support (D. B. Wilson et al., 2000). In contrast, findings from some experimental and randomized studies suggest that selection bias explains the observed negative relationship between work and crime among former offenders (Bushway & Apel, 2012; Skardhamar & Telle, 2012).

Intermittent labor force detachment may reflect the cumulative impact of institutional barriers and personal characteristics that lead former prisoners to perceive that there are no jobs available for them (Apel & Sweeten, 2010b). Persistent labor force detachment may identify men who are least committed to finding work, but only a few studies have examined whether labor force exit is associated with increased recidivism risk (Apel & Sweeten, 2010b; Crutchfield & Pitchford, 1997). Related to this, studies have not examined whether consistent attachment to the labor force—whether in the form of stable employment at one job, stable employment over time, or committed job-seeking efforts—functions as a reliable signal of offenders' desistance from crime (Bushway, 2003; Bushway & Apel, 2012). Finally, research and theory suggest that characteristics associated with "good" jobs (e.g., employment stability, decent wages, and fringe benefits) are responsible for the crime-reducing benefits of regular employment (Mocan, Billups, & Overland, 2005; Uggen, 1999; van der Geest et al., 2011). Few studies provide detailed information about the jobs prisoners find in terms of wages, fringe benefits, and opportunities for growth (Crutchfield & Pitchford, 1997; Grogger, 1998; Uggen, 1999; van der Geest et al., 2011).

Chapter 2: Theoretical Perspectives

This chapter introduces the rational choice perspective that underpins microeconomic models of crime (Becker, 1968; Coleman, 1988; Ehrlich, 1973; Heckman, 1976; Heckman, Stixrud, & Urzua, 2006; Lochner, 2004; Sickles & Williams, 2008). The first section presents the rational choice model of crime as work (Becker, 1968). The second section illustrates how scholars have integrated human, social, and criminal capital into a dynamic model of crime that explains variations in men's level of offending over time (Coleman, 1988; Ehrlich, 1973; Heckman, 1976; Heckman et al., 2006; Lochner, 2004; Mocan et al., 2005; Sickles & Williams, 2008). The last section presents the current study's proposed conceptual model.

2.1 Rational Choice Theoretical Framework

Rational choice models presume that people behave rationally in pursuing ends that maximize subjective expected utility (Apel, 2013; Becker, 1968; Ehrlich, 1973; Mocan et al., 2005). Individuals select an optimal balance of work and crime to maximize consumption and leisure (Grogger, 1998; Mocan et al., 2005). Crime and legal work are equivalent in that both produce income and limit time available to pursue other activities (Grogger, 1998; Mocan et al., 2005; Thornberry & Christenson, 1984). Criminal activity offers marginal offenders an alternative to legal work (Bushway, 2011; Thornberry & Christenson, 1984).

Men enter the labor force and seek market employment when their market wage exceeds their reservation wage. Men's reservation wage can be estimated by the marginal rate of substitution for their first hour of work, the point at which all time is allocated to leisure. Their marginal rate of substitution is a function of their market wages, hours spent in market work, hours spent in criminal activity and available sources of non-labor income (Ehrlich, 1973; Grogger, 1998; Williams & Sickles, 2002).

Non-labor income reduces men's incentives to seek wage employment, whether earned illegally or acquired legally in the form of savings and investments, family assistance, or social benefits (Grogger, 1998; Skardhamar & Telle, 2012). Men commit crimes when the returns on their first hour of crime are expected to exceed their market wage. Men will engage in crime up to the point at which their marginal returns to crime no longer exceed their market wage (Becker, 1968; Fagan & Freeman, 1999; Grogger, 1998; Williams & Sickles, 2002).

2.1.1 Objections to the Basic Model

The basic microeconomic model describes incentives that lead people to engage in financially motivated crimes, for which returns to crime can be monetized (e.g., drug sales, prostitution, property offenses) (Ehrlich, 1973; Grogger, 1998). However, on the surface many crimes do not meet this criterion, even if financial considerations played a role (e.g., domestic violence exacerbated by financial problems in the home). Strict utility maximization can be relaxed to include non-financial considerations: Perpetrators derive non-financial benefits from crime, including stress relief and social respect (Mocan et al., 2005; Sickles & Williams, 2008). Non-pecuniary considerations that influence individuals' assessments of the relative utility of crime include emotional wellbeing, interpersonal relationships, and social standing in the community (Ehrlich, 1973; Grogger, 1998; Sickles & Williams, 2008; Thornberry & Christenson, 1984).

Describing offenders' decision-making processes as rational may seem a fundamental mischaracterization, as ample evidence shows that most current and former prisoners assess situations poorly (Apel, 2013; Bucklen & Zajac, 2009; Nagin, 2007). Expected benefits are more salient than perceived risks, and many people are poorly equipped to estimate both the probability that they will be caught and the amount of pain they will feel if caught and punished. In light of uncertainty about their realistic job prospects, former prisoners employ heuristics to estimate perceived benefits from employment in determining whether to look for work (Apel, 2013; Bucklen & Zajac, 2009). Heightened emotional states reduce the extent to which they consider relevant costs of crime (Bucklen & Zajac, 2009; Nagin, 2007).

Nonetheless, choices that current and former prisoners make are rational in the sense that men's choices are informed by this general utility-maximization framework. Cognitive limitations, emotional distress, and drug use may reduce the accuracy with which former prisoners assess available opportunities, but these situational conditions do not undermine the basic assumption that men use means-end reasoning to bring about the best consequences for themselves (Apel, 2013; Bucklen & Zajac, 2009; Clarke & Cornish, 1985; Felson et al., 2012).

Heckman (1976) cautions against interpreting rational choice theoretical models literally. His savings model includes human capital investment, labor income, and leisure time as distinct activities, even though work hours and time spent on human capital investment overlap when people receive on-the-job training (Heckman, 1976). Similarly, time spent in criminal activity may overlap with leisure time without significant challenges to the general theoretical model. Nonetheless, this overlap may have implications for men's probability of recidivism. Men who consider criminal activity to be a form of leisure, as well as a form of work, may derive increased utility from crime, and this should strengthen their resolve to persist in criminal activity.

2.2 Dynamic Human Capital Model of Criminal Activity

Individuals vary in their skill levels, learning ability, social networks, and criminal ability (Lochner, 2004; Mocan et al., 2005). These endowments influence men's later decisions to engage in crime, work, and human capital investment. Individuals with high learning ability will enjoy greater returns to human capital investment than less-skilled individuals will (Mocan et al., 2005). Criminal ability should not influence the return on legal human capital investment, but it should influence the likelihood that men invest in human capital (Lochner, 2004).

2.2.1 Human Capital Investment

Human capital investment should increase men's incentives to enter the labor market and resist crime (Lochner, 2004). Men invest in education or job skills training to maximize lifetime earnings through skills acquisition. These investments initially reduce the time available for men to engage in crime or work. However, improved earnings prospects reduces future criminal involvement because men perceive that they have more to lose from crime if detected (Lochner, 2004; Mocan et al., 2005). Even criminally involved men may decide to reallocate income from consumption toward savings when they perceive larger potential gains from legal employment than ongoing criminal activity. Voluntarily reallocating a portion of current income from consumption to savings reduces men's dependence on crime in the future and facilitates later investments in legal human capital (Mocan et al., 2005).

2.2.2 Social Capital Accumulation

Social capital is a resource, akin to human capital, that accumulates over time and can help men obtain desired goods (Williams & Sickles, 2002). Unlike human capital, it is not held within an individual but is instead stored in men's relationships with other people (Coleman, 1988; Sickles & Williams, 2008). As a result, this socially embedded resource both facilitates and constrains men's actions. Men who maintain close attachments to prosocial individuals and institutions benefit from access to financial resources and emotional support in times of need (Coleman, 1988). However, these embedded social networks entail obligations from men. Failure to live up to these expectations causes men to experience more serious social sanctions than if they had not been embedded in social support networks (Coleman, 1988; Sickles & Williams, 2008; Williams & Sickles, 2002).

Men with more prosocial social capital risk greater losses from crime due to detection and punishment, and this process of embeddedness into prosocial networks strengthens men's commitment to conformity (Sampson & Laub, 2003; Sickles & Williams, 2008). Social norms, personal attachments to family and friends, and stigmatizing processes (e.g., depreciated social capital and loss of social support following arrest) increase the disutility from crime in proportion to men's accumulated social capital and the anticipated severity of punishment (Sickles & Williams, 2008).

2.2.3 Criminal Capital Accumulation

Men acquire criminal capital in the course of engaging in crime. Extensive criminal involvement increases men's criminal capital more quickly, and skilled offenders who avoid detection accumulate more capital than offenders who do not evade detection (Mocan et al., 2005). Involvement in licit and illicit activity permits men to build human and criminal capital simultaneously, and criminal activity may enhance men's legal human capital separate from any criminal capital gains. As with human capital, criminal capital deteriorates over time (Lochner, 2004; Mocan et al., 2005).

Extensive criminal capital increases the amount of time men invest in criminal activity. Criminal human capital reduces men's relative risk of incarceration, but this is offset by increased risk of detection as their involvement in crime increases. Criminal capital may increase while men are imprisoned if they learn skills from spending time with other prisoners; for other men, criminal capital declines during that time due to the reduction in available criminal opportunities. Men who leave prison with higher levels of criminal than legal human capital have greater incentives to engage in crime over legal employment. Prison programs that increase men's legal human capital increase men's incentives to engage in legal employment (Mocan et al., 2005). Increasing former prisoners' expected benefits from employment, thereby increasing the opportunity cost of crime, may reduce recidivism upon release (Mocan et al., 2005; Nagin, Cullen, & Jonson, 2009).

2.3 Proposed Conceptual Model

Figure 2.1 depicts pathways by which prison education and employment programs strive to reduce recidivism by strengthening men's attachments to the labor force (Farabee et al., 2014; Redcross et al., 2012; Saylor & Gaes, 1997). Education and employment programs improve men's job prospects through job skills training and the acquisition of education credentials (Duwe & Clark, 2014; Steurer, Smith, & Tracy, 2001; Tyler & Kling, 2007; D. B. Wilson et al., 2000). Human capital accumulation improves men's wage prospects and increases their incentives to take legal work (Thornberry & Christenson, 1984). Full-time employment in the formal labor market provides men with living wages, benefits, and opportunities for growth and career advancement (Bloom, 2006; Hagan, 1993).

Ongoing stable employment enhances men's financial wellbeing. Jobs that pay living wages alleviate financial strains that can lead men to commit economic crimes (Felson et al., 2012; Skardhamar & Telle, 2012). Financial wellbeing contributes to enhanced emotional wellbeing (Harris, Evans, & Beckett, 2010). Sustained emotional and financial wellbeing facilitate desistance among former prisoners who find and maintain work (Bucklen & Zajac, 2009; Felson et al., 2012).

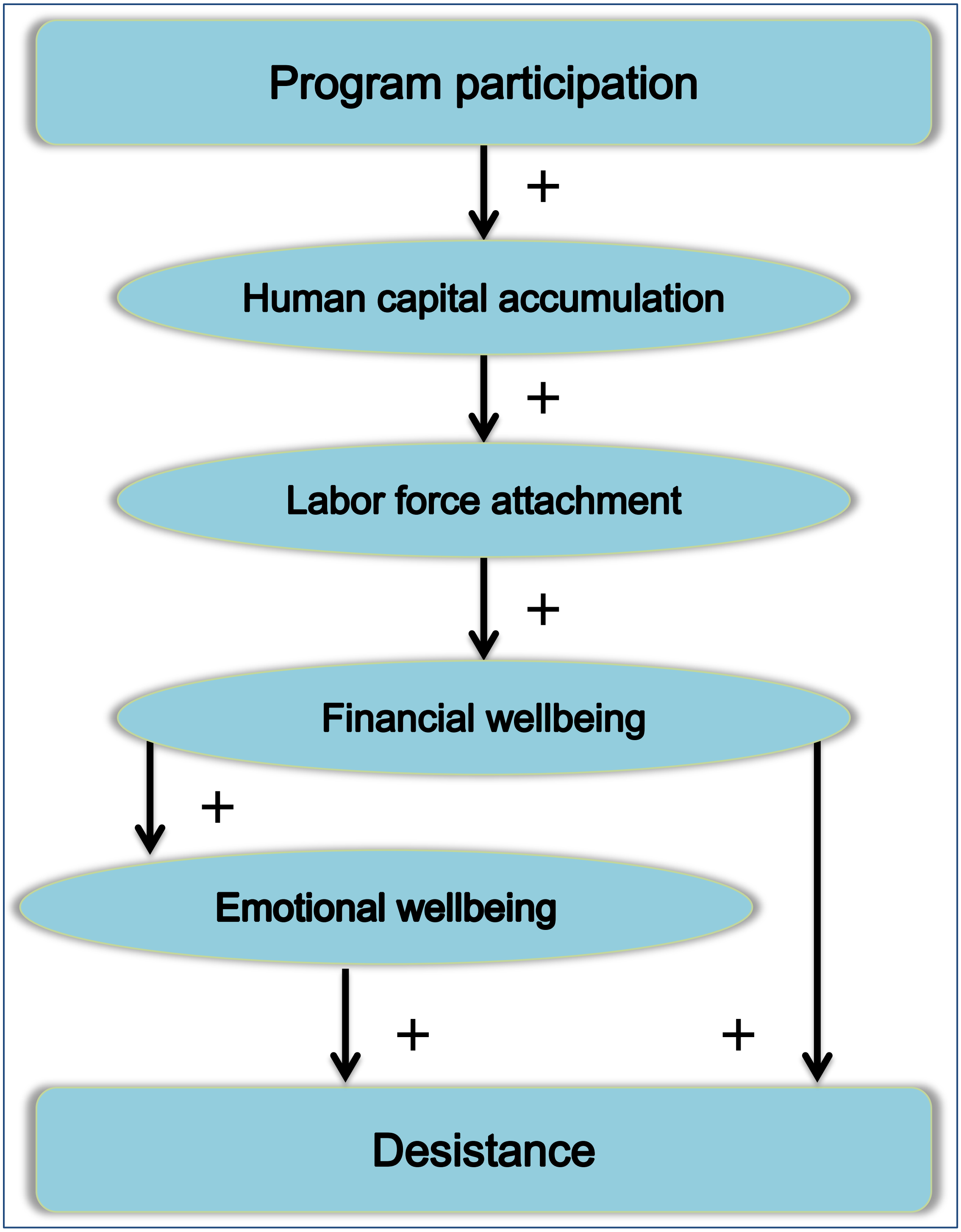


Figure 2.1 Program Participation, Labor Force Attachment, and Desistance.

Figure 2.2 presents the original conceptual model used to guide the structural equation path analytic model. The path model tests whether labor force participation and quality employment reduces men's risk of recidivism. Entering and remaining in the labor market as an unemployed job candidate necessitates costs, and people who do not feel committed to finding work are unlikely to perceive that these costs are worth the effort (Crutchfield & Pitchford, 1997). Unemployed and low-wage workers are more responsive to criminal opportunities than are stably employed workers who earn high wages (Crutchfield & Pitchford, 1997; Sickles & Williams, 2006; Thornberry & Christenson, 1984; Williams & Sickles, 2002). Individual-specific factors, such as low expected wages, dislike of work, and wage garnishments for legal or child support debt, facilitate criminal activity by lowering the threshold at which benefits exceed costs (Harris et al., 2010).

Larger socioeconomic conditions (weak labor markets, recession, and structural unemployment) can further reduce the opportunity cost of crime for some people (Thornberry & Christenson, 1984). Periods of unemployment and economic recessions increase the amount of time men spend on criminal activity. Prolonged periods out of the labor force enable some men to gain sufficient criminal capital to justify persisting in crime after the recessionary period (Mocan et al., 2005). Illicit activity can provide higher remuneration than legal employment for young, low-skilled men with prison records. Former prisoners who cannot find legal work that meets their reservation wages may exit the labor force to pursue illicit opportunities (Apel & Sweeten, 2010b; Fagan & Freeman, 1999; Pettit & Lyons, 2009; Visher, Debus-Sherrill, & Yahner, 2011).

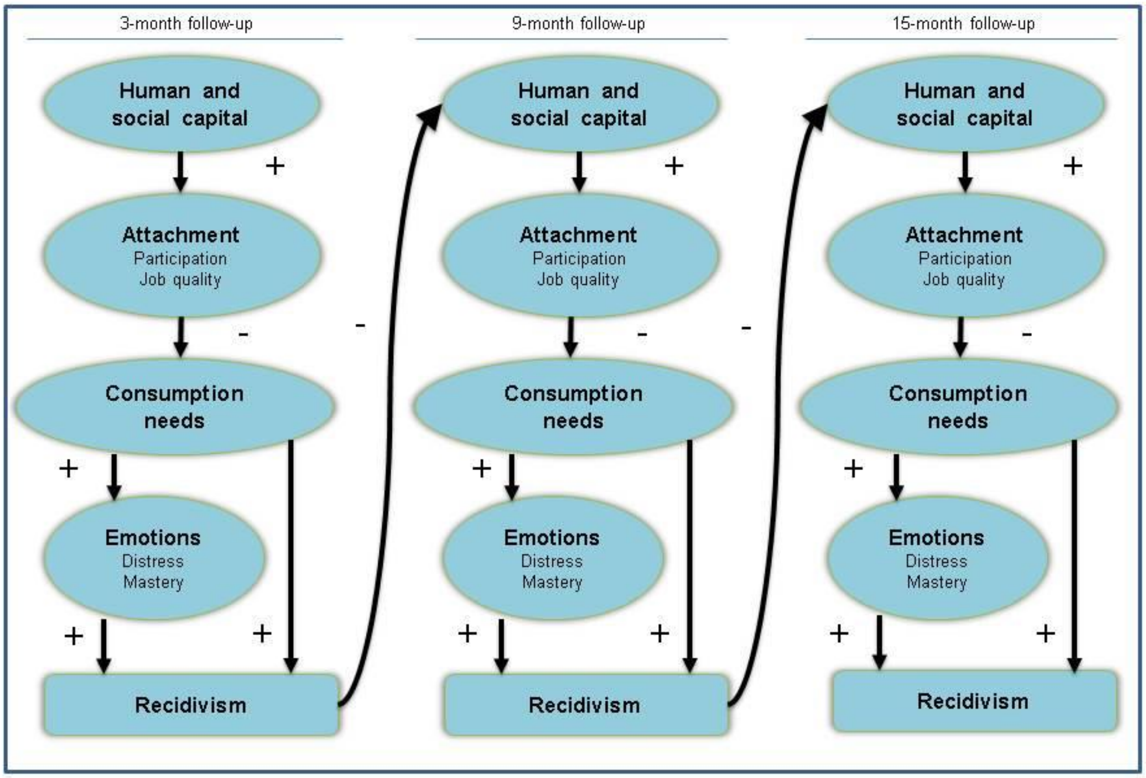


Figure 2.2 General Panel Model of Post-Release Labor Force Attachment and Recidivism.

Incarceration and criminal justice involvement contribute to later unemployment by severing men's connections to employers (Hagan, 1993; Krohn, Ward, Thornberry, Lizotte, & Chu, 2011; Stewart, 2007; Western, 2002). Removal from the legal labor market depreciates men's stock of human and social capital, effectively making them less employable in the future (Heckman & Borjas, 1980; Mocan et al., 2005; Stewart, 2007). Jobless applicants often need to accept reduced wages to reenter the labor force (Stewart, 2007). People who experience early job loss experience longer, recurrent periods of unemployment (Heckman & Borjas, 1980; Thornberry & Christenson, 1984). This reduces the number of hours worked in the formal labor market and flattens long-term earnings trajectories (Stewart, 2007).

Labor force detachment and unemployment expose former prisoners to financial and psychological strains that may explain much of the relationship between work and crime. The stress associated with looking for work compounds as the length of unemployment increases (Krueger, Mueller, Davis, & Sahin, 2011; Sugie, 2014; Young, 2012). Repeated job rejections diminish applicants' self-confidence and reduce their motivation to continue looking for work (Krueger et al., 2011; Sugie, 2014; Young, 2012). Ongoing financial and emotional stressors trigger a cascade of negative emotional states that reduce men's sense of personal mastery and increase their risk of recidivism (Halvorsen, 1998; Maruna, 2001; Price et al., 2002; Visher et al., 2011).

Chapter 3: Methodology

3.1 Overview

Prior SVORI evaluations concluded that employment services failed to improve participants' reentry outcomes, and in some cases appeared to increase recidivism risk (Lattimore et al., 2012; Lattimore et al., 2009). I first examine whether unobserved heterogeneity contributes to inconsistent estimates of the effects of employment-focused programs on post-release employment and crime (Heckman et al., 2000; Sedgley et al., 2010). Group-based trajectory modeling (GTM) and propensity score techniques (PSM) use men's baseline interviews and criminal history records to control for characteristics that differentially select individuals into treatment (Haviland, Nagin, & Rosenbaum, 2007).

Second, I use duration models to examine whether education and employment programs effect participants' time to first rearrest (Sedgley et al., 2010). Third, I examine whether increased labor force attachment leads to higher quality employment (Stewart, 2007), increased financial and emotional wellbeing (Price et al., 2002), and reduced offending (Thornberry & Christenson, 1984). The structural equation model use follow-up interview and administrative arrest data to test whether quality jobs increase men's financial and emotional wellbeing and reduce their risk of recidivism (Thornberry & Christenson, 1984).

3.2 Research Hypotheses

The first set of hypotheses examines the effects of participation in employment-focused prison programs on men's time to rearrest. The services included in this definition are educational programs and job training/vocational education programs (Heckman, 2001; Sedgley et al., 2010).

1. Men who participate in vocational education, job training, or other education programs exhibit distinct pre-release characteristics from men who do not receive these services.
2. After controlling for observed heterogeneity between nonparticipants and participants, program participants exhibit lower recidivism rates than similar nonparticipants.
3. Participation in more than one type of employment-focused program has diminishing marginal benefits on recidivism.

The second set of hypotheses examine the effects of labor force attachment and job quality on men's financial and emotional wellbeing, and their risk of recidivism during the early reentry period (Bucklen & Zajac, 2009; Price et al., 2002; Skardhamar & Telle, 2012; Stewart, 2007; Thornberry & Christenson, 1984).

4. Criminal justice involvement (e.g., arrest during the prior wave) reduces men's stock of human and social capital.
5. Men who have high levels of human and social capital are more likely to participate in the labor market than men with low levels of capital are.
6. Increased labor force participation leads to improved job quality.
7. High quality employment reduces men's experience of financial strain (e.g., unmet consumption needs).
8. Unmet consumption needs increase the probability that men reoffend.
9. Financial strain, characterized by unmet consumption needs, diminishes emotional wellbeing (e.g., psychological distress, personal mastery).
10. Diminished emotional wellbeing increases the likelihood that men reoffend.

3.3 Research Design

3.3.1 Data Collection

The study uses data on adult male prisoners from the Serious and Violent Offender Reentry Initiative (SVORI) multi-site evaluation (n = 1,697). This collaborative federal effort provided grant funds to 69 state agencies to design comprehensive reentry services targeting serious and violent offenders under 35 years old. The SVORI evaluation tested the success of this federal funding stream in motivating states to develop comprehensive reentry services that reduce recidivism. SVORI programs varied widely in design, curriculum, activities, intensity, and timeframe because agencies receiving SVORI funds could tailor services to fit the local context without following a specific reentry-programming model (Lattimore et al., 2012; Lattimore & Steffey, 2009).

The evaluation used an intent-to-treat design, in which respondents were classified as participants and nonparticipants based on enrollment in SVORI programs or residence in facilities offering SVORI programs. Sites recruited otherwise eligible individuals into the non-SVORI comparison sample from facilities that did not provide SVORI programs. They also recruited otherwise eligible individuals returning to communities without SVORI programs. Not all SVORI participants received reentry services, and non-SVORI participants receiving "treatment as usual" could participate in similar non-SVORI services (Lattimore & Steffey, 2009). Data on program participation were not available from all SVORI sites and for all SVORI nonparticipants, so the evaluation uses men's responses at the baseline interview (Lattimore et al., 2012).

The 12 states offering SVORI-funded services to adult men that participated in the SVORI evaluation were responsible for recruiting SVORI participants and comparable nonparticipants into the study. Only two states randomly assigned men to the treatment and comparison groups. The remaining 10 states enrolled eligible and interested men into SVORI programs and then enrolled otherwise similar individuals into the comparison group. The initial pool of eligible adult male prisoners included 2,564 adult men returning home from adult prisons between July 2004 and November 2005. Twelve percent of eligible men refused to participate in the study (*n* = 295), 21% were released from prison before completing the baseline interview (*n* = 538), and 1% were ruled ineligible due to language or cognitive limitations (*n* = 34) (Lattimore & Steffey, 2009).

Men completed baseline interviews roughly 1 month before release from prison, and evaluators contacted the men at 3, 9, and 15 months after release to complete follow-up interviews. The follow-up interviews were completed from October 2004-April 2006, April 2005-October 2006, and October 2005-April 2007. Men received financial incentives for follow-up interviews completed in the community: $35 at the 3-month interview, $40 at the 9-month interview, and $50 at the final 15-month interview. They received an additional $5 if they called a toll-free number to schedule follow-up interviews. Men who were incarcerated at the time of follow-up interviews completed interviews in prison. When possible, respondents who completed interviews while institutionalized received the same financial compensations. Study participants who completed all four interviews received an additional $50 at the end of the study (Lattimore & Steffey, 2009).

3.3.2 Sample

The original SVORI evaluation sample included 1,697 men who were recruited from prison sites in 12 US states. As part of the original evaluation, the Federal Bureau of Investigation (FBI) National Crime Information Center (NCIC) provided lifetime arrest data for men in 11 of 12 states (*n* = 1,575). Arrest data spanned men's full criminal history up to 36 months after release from the SVORI status incarceration. The NCIC provided the dates of each arrest as well as the charge and conviction offense associated with the arrest. SVORI evaluators calculated the time from arrest to release from prison for each arrest recorded in the NCIC database (Lattimore et al., 2012; Lattimore & Steffey, 2009).

Roughly 58% of these men completed the 3-month interview (*n* = 919), 61% completed the 9-month interview (*n* = 957), and 65% completed the 15-month interview (*n* = 1,030). However, only 43% of men interviewed at the pre-release baseline interview completed all three waves (*n* = 670) and 21% of men completed no interviews after the pre-release interview (*n* = 330) (Lattimore et al., 2012; Lattimore & Steffey, 2009).[1]

The initial sample for this study comprises 1,575 cases that had valid pre-SVORI arrests recorded in the NCIC arrest records files. These men were included in the group-based trajectory model (*n* = 1,575) and logit participation model (*n* = 1,571). Cases that were successfully matched using propensity scores were included in the duration models (*n* = 1,521). Figure 3.1 presents the sample selection process used to identify latent trajectory groups, model participation status, and select appropriate matches among participants and nonparticipants.

The longitudinal structural equation model uses responses from three follow-up interviews. Individuals who completed one or more follow-up interviews were retained in the longitudinal structural equation model (*n* = 1,245).

[1] The original SVORI sample included 122 individuals who had no pre-SVORI arrests recorded in the NCIC arrest records file. Nearly all of these men were imprisoned in Maine (*n* = 79), which does not report arrests to the National Crime Information Center. The remaining men with no NCIC-reported arrests were released from the other states' sites. The attrition rates from the follow-up interviews for the non-NCIC sample were virtually indistinguishable from the NCIC sample, suggesting that attrition was not necessarily associated with state-level factors.

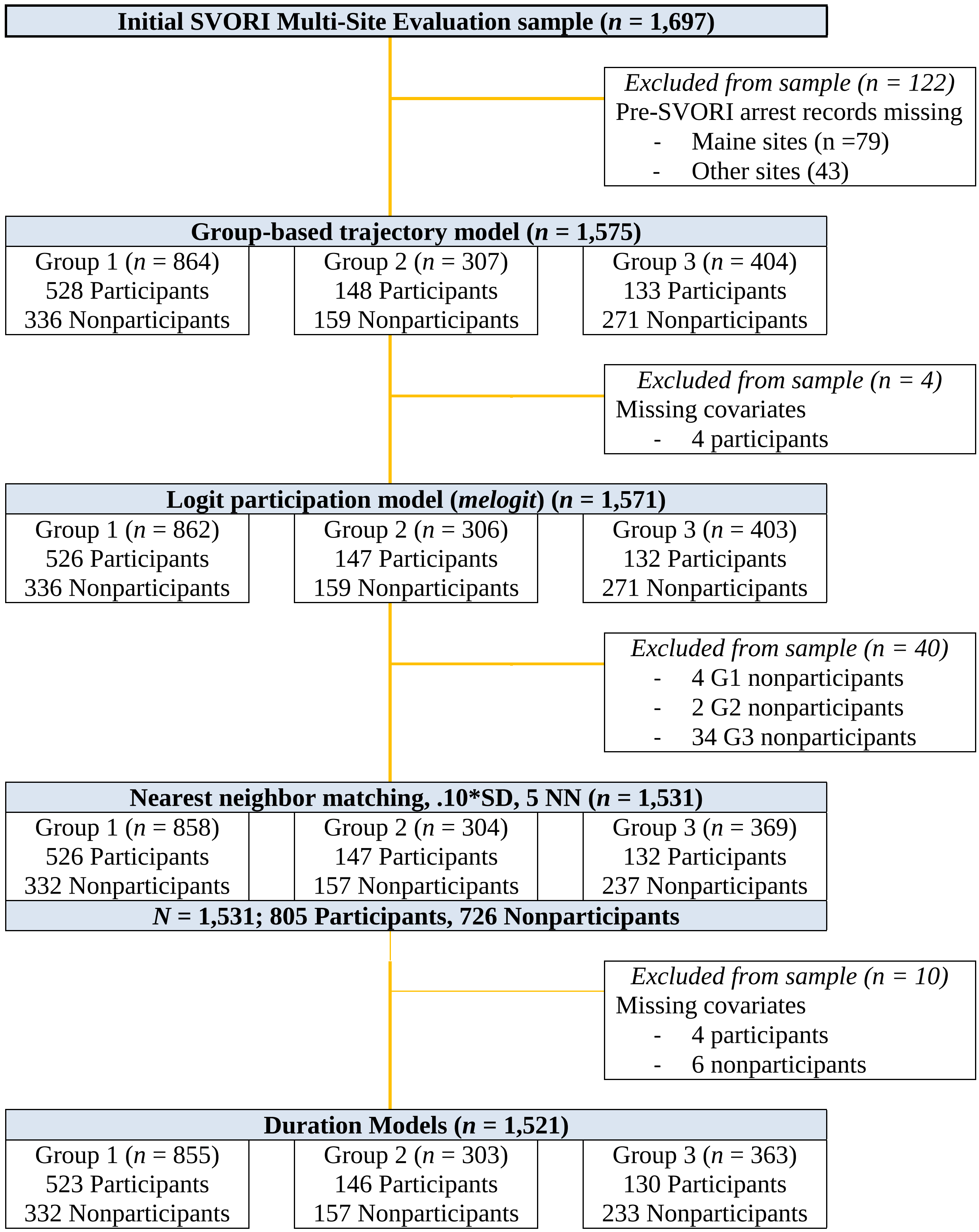


Figure 3.1 Sample Selection Flowchart for Duration Models.

3.3.3 Missing Data Analysis

Indicators for Missing Data on Baseline Covariates

Certain key demographic variables that had limited numbers of missing data were recoded to retain cases with intermittent missing data. Two individuals who had missing data for racial/ethnic status were included in a combined category: Hispanic, biracial/multiracial, other racial/ethnic status, or missing. Nine individuals who were missing data on number of times previously imprisoned were included in the category for no previous prison terms, due to their young ages when entering prison to complete their SVORI-related sentences.

Group-Based Trajectory Model

The trajectory model retained cases that had missing data for some observation periods (in cases where men were too young to have been eligible for arrest), but these cases contributed fewer observation periods to the fitting of the trajectory model. Approximately half of the time-invariant explanatory variables included in the trajectory model were created using lifetime arrest records. The remaining time-invariant explanatory variables come from the baseline interview, which was completed by all of the men recruited into the sample. However, most items had little or no missing data. Categorical variables that had missing data for a small number of cases (e.g., racial/ethnic status, previous imprisonments) were recoded as described above to retain cases.

Propensity Score Matching and Duration Models

The indicator for participation status had no missing data (n = 1,575): One man did not indicate whether he had received vocational education/job training, but all of the men provided information on educational service receipt. The duration models use data from official arrest records that were compiled for all men in the original sample (n = 1,575). The multilevel logit model and duration models used listwise deletion, due to incidental patterns of missing data for items collected at the baseline interview. These models include race and prison variables that were recoded to retain cases with missing data, as described previously. The logit participation model eliminates four cases with missing data on covariates in the model (*n* = 1,571). The duration models exclude 10 cases from the matched sample that had missing data on covariates (*n* = 1,521).

Confirmatory Factor Analysis

The maximum likelihood (ML) estimation procedure retained cases with incidental missing data patterns, although cases with extensive missing data (e.g., attriters from all three follow-up interviews) were excluded from the sample.

Structural Equation Modeling

This study uses full-information maximum likelihood (FIML) estimation for the structural equation models, which assumes that data are missing at random (Allison, 2003; Yuan, Yang-Wallentin, & Bentler, 2012). FIML estimation using the full sample is preferable to statistical techniques that use complete cases when data are not completely missing at random (Allison, 2003). Listwise deletion introduces the possibility of bias into estimates, while the reduced sample size increases the size of standard errors and reduces the power of hypothesis tests (Allison, 2003). FIML generates parameter estimates that are often more efficient than multiple imputation techniques and do not rely on multiple random draws of data sets (Allison, 2003, 2012; Larsen, 2011). Because FIML addresses missing data as part of the estimation process, the parameter estimates, standard errors, and test statistics are stable and do not vary (Allison, 2012).

Table 3.1 Variable Descriptions by Analysis

Variable	GTM	PSM	DM	LSEM
In-person interviews				
Linear age at release	X	X[a]	X[a]	X
Squared age at release	X			
Cubed age at release	X			
Years of education		X[a]	X[a]	X
Racial/ethnic status (*ref.* African American)				
White	X	X	X	X
Hispanic, multiracial, other, miss	X	X	X	X
SVORI term: Sentencing offense				
Drug offense		X	X	X
Property offense		X	X	X
Person/violent offense		X	X	X
Parole/probation violation	X		X	X
SVORI term: Time served (years)			X[a]	X
Log-transformed time served		X[a]		
Prior prison terms		X		
No previous terms/missing	X		*ref.*	*ref.*
1 previous term	X		X	X
2 previous terms	*ref.*		X	X
3 or more previous terms	*ref.*		X	X
Pre-SVORI income: Family		X		
Pre-SVORI: Longest job (*ref.* Never/1 year)				
1 to under 2 years		X		X
2 to under 5 years		X		X
More than 5 years		X		X
Prosocial peers (W2-W4)				X
Job search difficulties (W2-W4)				X
Stable employment (W2-W4)				X
Recent job: Hours worked (W2-W4)				X
Recent job: Permanency (W2-W4)				
Permanent position				X
Temporary employment				X
Recent job: Stability (W2-W4)				
Formal pay				X
Casual pay/self-employment				X
Financial need items (W1-W4)				X
Personal mastery scale			X	
Average anxiety score (W1-W4)				X
Average depression score (W1-W4)				X
Average hostility score (W1-W4)				X
New crime (SR, W2-W4)				X

Table 3.1 Variable Descriptions by Analysis

Variable	GTM	PSM	DM	LSEM
In-person interviews				
Pre-SVORI recent alcohol/drug use			X	X
Global Severity Index			X	
General physical health status		X		
Health limits activities (*ref.* None)				
A little		X		
A lot		X		
SVORI participant status		X		
Educational program participation			X	
Employment program participation			X	
Prison industry job			X	
Work release job			X	
SVORI site location (*ref.* South Carolina)		Level-2		
Iowa		random	X	X
Indiana		effect	X	X
Kansas			X	X
Maryland			X	X
Missouri			X	X
Nevada			X	X
Ohio			X	X
Oklahoma			X	X
Pennsylvania			X	X
Washington			X	X
NCIC Arrest Files				
Pre-release arrest files				
Age at first arrest	X		X	
Lagged arrest, drug offense	X	X		
Lagged arrest, property offense	X	X		
Lagged arrest, violent offense	X	X		
Years with any recorded arrest	X			
Lifetime sum of recorded arrests	X	X		
Arrests count, year before prison			X	X
Post-release arrest files				
Time to first arrest			X	
Time to first drug arrest			X	
Time to first property arrest			X	
Time to first violent arrest			X	
Arrest within 3, 9, 12 months				X
Return to prison within 3, 9, 15 months				X

Table 3.1 Variable Descriptions by Analysis

Variable	GTM	PSM	DM	LSEM
Model-Generated Variables				
Trajectory group (*ref.* Group 1)				
Group 2		X	X	X
Group 3		X	X	X
Linear age*Trajectory group		X[a]		
Education*Trajectory group		X[a]		
Prison terms*Trajectory group		X		
Prob. participation, Education/Employment services			X	
Probability of participation* Trajectory group			X	

Note: GTM = Group-based trajectory model. LSEM = Longitudinal Structural Equation Model. NCIC = National Crime Information Center. PSM = Propensity score methods. DM = Duration Models. SR = Self-report. SVORI = Serious and Violent Offender Reentry Initiative. In-person interview items were collected at baseline unless noted. "a" indicates continuous variables centered on state means.

3.4 Measures

This section first describes the main outcomes variables for the study. It next describes the explanatory and outcome variables for each set of analyses in detail. Table 3.1 presents the variables included in each type of analysis. Variables included in the analyses can be divided into three categories: in-person interview items, variables created from the NCIC arrest record files, and model-generated variables. Most covariates from the in-person interview were measured at the baseline interview; variables that were obtained from the follow-up interviews are noted in Table 3.1.

3.4.1 Main Outcome Variables

This study use official records and men's self-reported information from follow-up interviews to measure criminal activity and criminal justice involvement. *Arrests* (for any offense and by specific offenses) are measured using the NCIC arrest records, and *self-reported criminal activity* (offenses committed during the 3-6 month reference period for each follow-up wave) is measured using responses from each follow-up interview (Loeffler, 2013; Zweig, Yahner, & Redcross, 2011).

3.4.2 Group-Based Trajectory Model

Measures included in the trajectory model were obtained from NCIC arrest records data and from the baseline pre-release interview.

Outcome Variables

The key outcome variables (e.g., indicators of annual arrests) are derived from the NCIC arrest record files. The trajectory model uses indicators of annual arrests during the 14 years leading up to the SVORI status incarceration to chart prisoners' prior offending trajectories (Haviland & Nagin, 2005; Haviland et al., 2007; Thornberry & Christenson, 1984).

Explanatory Variables

The trajectory model includes time-varying and time-invariant measures created from the longitudinal arrest record files. Linear, squared, and cubed forms of age at the time of the arrest were included to model the nonlinear effect of age on risk of arrest. Age at arrest was estimated using men's age at release from the SVORI status offense. Time-varying covariates included in the model were binary indicators of drug, property, or violent arrests during the prior year (e.g., three lagged indicators for each year, indicating the presence of a drug, property, or violent arrest the previous year).

Additional covariates for criminal history were included in the model to control for false desistance, observed during periods when men were imprisoned, and to control for the fact that the 14-year observation period excluded some men's complete criminal records. Time-invariant covariates that were created using NCIC arrest records include age at first NCIC arrest (continuous), number of pre-SVORI years with any arrests (continuous), and lifetime number of arrests before SVORI prison term (continuous).

Other time-invariant covariates were obtained from the baseline in-person interview. To control for the possibility of false desistance during previous periods of imprisonment, the model includes self-report indicators for number of times imprisoned (1 = first imprisonment or missing, 2 = second imprisonment, *ref.* two or more previous imprisonments) and for parole or probation violation leading to the SVORI prison term (Eggleston, Laub, & Sampson, 2004). Racial/ethnic status is included in the model to control for differential policing practices and unobserved state-level differences (1 = Caucasian, 2 = African American (*ref.*), 3 = Hispanic, biracial/multiracial, other racial/ethnic status, or missing).

3.4.3 Multilevel Logit Participation Model

The propensity score model includes pre-release indicators of men's demographic characteristics, prior employment, criminal history, and structural factors that may be correlated with men's decision to participate in employment-focused prison programs (Apel & Sweeten, 2010a; Haviland et al., 2007). Measures included in the logit participation model were obtained from NCIC arrest record files and from the baseline pre-release interview.

Outcome Variables

Participation status was measured as participation in educational services or specific employment programs while imprisoned. Educational services ranged from literacy tutoring and GED courses to higher education (n = 717). Employment programs included vocational education or job training programs (n = 208). Some participants received both educational and employment services (n = 116). Nearly half of the sample did not participate in either type of program (n = 766).

Explanatory Variables
SVORI site location (US states) is included in the model as a level-2 random effect. Individuals are nested within states from which they had been released from prison.

Level-1 variables measure individuals' characteristics. Demographic variables were age at release (continuous), education (continuous), racial/ethnic status (*ref*. African American), and previous family income support (1 = yes). Four items reflected the SVORI status offense: number of years in prison for the SVORI status offense (log-transformed) and three indicators for drug, property, and violent conviction. Several items captured pre-SVORI criminal justice involvement: previous imprisonments, indicators for drug, property, or violent arrests during the year preceding prison entry (1 = yes), and total number of arrests that year (continuous).

Other explanatory variables included SVORI participation status (1 = yes), general physical health (health limits moderate activity: 1 = a lot, 2 = a little, *ref*. not at all), and general emotional wellbeing (e.g., feeling calm and peaceful). Trajectory group membership was included in the model as dummy variables (*ref*. Group 1) and as interaction terms for age, education, and continuous number of previous imprisonments. Age at release, education, and prison sentence length were centered on state means to account for state-level differences.

3.4.4 Duration Models
Measures included in the duration models were obtained from NCIC arrest records data and from the baseline pre-release interview.

Outcome Variables
The main outcome measure for the duration models was time to rearrest for any offense, using post-release arrest records obtained from the NCIC arrest files. Time to arrest was measured in days since release from the SVORI prison term. The parametric duration models measure time

to arrest in five different formats: time to arrest within the first 3 years, with repeated failures permitted; time to first arrest for any offense; and time to first arrest for three offense subtypes (drug, property, and violent offense). Prior to fitting the models, the five continuous arrest measures were log-transformed to normalize their distributions and improve the fit of the models. The duration models use the log-transformed continuous arrest measures as outcome variables. In each case, model residuals indicate that the models fit most of the observations well.

Explanatory Variables

Variables included in the duration models include indicators of program participation, men's pre-release demographic characteristics, work experience, prior offenses, and predicted trajectory group membership (Brewster & Sharp, 2002; Sedgley et al., 2010; Skardhamar & Telle, 2012). The duration models presented exclude interaction terms for engagement in both types of employment-focused programs, but results of models that include interaction terms are not substantively different.

The main predictor variables were educational programming, employment programming, trajectory group membership, and predicted probability of participation. Demographic and human capital measures included age at release (continuous), education (continuous), longest time employed at one job (1 = 1-2 years, 2 = 3-5 years, 3 = 5 or more years, *ref*. less than 1 year), work release employment (1 = yes), and prison industry employment (1 = yes). Measures for the SVORI status offense included three indicators for having been convicted of drug, property, and violent offenses, an indicator for parole or probation violations leading to the SVORI prison term, and prison sentence length (continuous).

Recent criminal history was captured using men's age at first NCIC arrest (continuous), total number of arrests the year preceding prison entry, and number of previous imprisonments (1 = one previous imprisonment, 2 = two or more previous imprisonments, *ref*. first imprisonment or missing). Physical and mental health items included personal mastery (continuous parcel averaging responses from eight baseline interview items), Global Severity Index (GSI) at baseline, and an indicator of alcohol or drug use during the month preceding the SVORI prison term (1 = yes). Racial/ethnic status (*ref*. African American) and state location (*ref*. South Carolina) are included in the model as controls for social structural context. Age at release, education, and prison sentence length were centered on state means to account for state-level differences.

3.4.5 Structural Equation Modeling

The model includes five analysis periods: the baseline interview (before release), the first 3 months following release, months 4-9, months 10-15, and recidivism measures for months 3-21. Table 3.2 presents the interview and data collection periods used to create the items included in the path models.

Indicators and measures included in the structural equation model come from the baseline interview, three follow-up interviews, and NCIC post-release arrest files. The LSEM uses measures from waves 2-4 for labor force participation, job quality, financial needs, psychological distress, and criminal activity (Krohn et al., 2011).

Latent Factors

Financial need (Time 1, 2, 3, & 4). The latent financial need factors were modeled using responses to six items at each interview period. Men stated the extent to which they needed financial assistance at the time (0 = not at all, 1 = a little, 2 = a lot). These ordinal-scale items were combined to form two parcels, the first of which averaged men's responses to three items (place to live, clothing banks/food pantries, financial assistance). The second parcel averaged men's responses to the following three items (transportation, public financial assistance, public healthcare insurance).

Table 3.2 Interview and Data Collection Periods for Longitudinal Structural Equation Model

Data source Reference period	Wave 1 Month of release	Wave 2 Months 1-3	Wave 3 Months 4-9	Wave 4 Months 10-15	NCIC files Months 1-21
Constructs					
Stable employment/ Job quality		Since release	Since date of last interview	Since date of last interview	
Financial needs	Date of interview	Date of interview	Date of interview	Date of interview	
Psychological distress	7 days preceding interview	7 days preceding interview	7 days preceding interview	7 days preceding interview	
Self-reported criminal activity		Since release	Since date of last interview	Since date of last interview	
Rearrest/ Return to prison		Within first 3 months	Within first 9 months	Within first 12 months	Within first 21 months
Control variables	Date of interview				
NCIC files *Analysis periods* Post-release months	1 0	2 1-3	3 4-9	4 10-15	5 16-21

Psychological Distress (Time 1, 2, 3, & 4). Psychological distress was measured for each time point using responses to 15 items measuring respondents' feelings of anxiety, depression, and hostility during the previous week (1-5 scale). The five items within each subscale were first averaged to create three parcels for each analysis period (before release, 3 months, 9 months, and

15 months after release). These parcels were then log-transformed to normalize their distributions.

Labor force attachment (Time 2, 3, & 4). Three items were used to model men's labor force attachment during the reference periods preceding each follow-up interview (van der Geest et al., 2011). The first item is included in the model as an observed indicator for labor force participation, and is not an indicator of the latent construct for job quality. The binary indicator of labor force participation measures stable employment since the date of the last interview (1 = having worked at least once during each month that men had been living in the community). Men who worked intermittently during the 3-6 month reference period were coded as 0, as were men either who did not work at all or who were not living in the community at any point during the observation period.

The latent construct for job quality is measured using two standardized items collected at each of the three follow-up interviews. The first item reflected the average number of hours men had worked each week at their last place of employment (centered and scaled to *M* 0, *SD* 1). The second item was an index of primary sector employment. The initial score ranged from 0-6 and was created by summing men's responses to three questions (Job permanency: 0 = no recent job, 1 = temporary pay, 2 = permanent employment; Job stability: 0 = no recent job, 1 = casual pay/self-employment, 2 = formal pay; Job benefits: 1 = receive paid time off, 1 = receive health insurance from work). This 6-point index was centered and scaled to *M* 0, *SD* 1.

Observed Variables

Criminal activity is measured by self-reported criminal behavior during the months leading up to each follow-up interview (Sickles & Williams, 2008; Williams & Sickles, 2002). Criminal involvement was measured at three time points. The first item recorded any crime committed since release from prison (W2, at approximately 3 months following release), the second reported crimes that occurred between the second and third interviews (W3, approximately 3-9 months after release), and the third recorded crimes committed since the third interview (W4, months 10-15). To supplement findings using self-reported criminal involvement, the model includes indicators for arrest within 12 months and return to prison within the first 21 months (Thornberry & Christenson, 1984).

Explanatory Variables

Control variables that were collected at baseline include age at release, educational attainment, racial/ethnic status (*ref*. African American), and longest time employed at one job (1 = 1-2 years, 2 = 3-5 years, 3 = 5 or more years, *ref*. less than 1 year). Measures for the SVORI status offense include three indicators for having been convicted of drug, property, and violent offenses, an indicator for parole or probation violations leading to the SVORI prison term, and prison sentence length (continuous). Criminal risk measures include trajectory group membership (*ref*. Group 1), total number of arrests the year preceding prison entry, number of previous imprisonments (1 = one previous imprisonment, 2 = two or more previous imprisonments, *ref*. first imprisonment or missing), and an indicator of alcohol or drug use during the month preceding the SVORI prison term (1 = yes). Dummies are included to control for state-specific characteristics (*ref*. South Carolina).

Covariates collected at follow-up waves capture men's recent human and social capital. These included parcels measuring the average number of job search difficulties respondents had faced during the reference period, and positive peer influences (proportion of friends employed, proportion of friends who stay out of trouble). Criminal justice indicators measure rearrests and returns to prison within the first 9 months of release from prison.

3.5 Data Analysis Plan

Persistent, chronic, and more serious offenders are less likely to have acquired work skills before prison entry and to pursue legal employment after release (Apel et al., 2007; Brame, Paternoster, & Piquero, 2012; Nagin & Tremblay, 2005). This study employs techniques that control for heterogeneity in treatment (program participation, labor force attachment) and in prior observations of the outcome (recidivism) that can bias estimates of the average treatment effect (Heckman, 2001; Heckman, Ichimura, & Todd, 1997). Group-based trajectory modeling and propensity score matching control for pre-SVORI factors that shaped men's access to services and informed their participation decisions (Apel et al., 2007; Haviland et al., 2007; Haviland, Rosenbaum, Nagin, & Tremblay, 2008; Heckman et al., 1997). Propensity score matching and duration models are used to test the first three hypotheses presented at the beginning of the chapter.

Structural equation modeling is used to test the remaining hypotheses (4-10). The structural equation model employs a cross-lagged recursive panel design to assess 1) whether labor force attachment is associated with self-reported criminal activity during the next interview period, and 2) whether self-reported criminal activity is associated with labor force attachment during the next interview period.

3.5.1 Group-Based Trajectory Model

The Stata user-written command *traj* was used to derive latent groups within the sample, using men's pre-SVORI arrest records. The trajectory modeling procedure uses time-varying outcome measures (binary indicators for any arrest within a given year) to identify distinct arrest trajectories. Time-varying covariates are included in the longitudinal component of the model, as these covariates may alter the shapes of the trajectories for certain groups. Time-invariant covariates are included in the multinomial component of the model; these characteristics differentiate members assigned probabilistically to each derived trajectory group. Men are assigned probabilistically to one group, based on their observed characteristics. Models' Akaike information criterion (AIC) and Bayesian information criterion (BIC) values were used to compare competing non-nested models to determine which one provided the best fit to the data. Appendix C provides detailed information about the estimation process.

Fitting the Trajectory Model

Age is the primary time-varying predictor in the model; it was included in the final model in linear, squared, and cubed terms. Including linear, squared, and cubed terms for age at time of arrest provided superior fit to models that included only the linear or squared terms. Time-varying lagged indicators for drug, property, and violent arrests were included in the model because their coefficients were significant for two of the three derived latent groups. Other time-invariant covariates were retained in the model because they improved the fit of the model and controlled for differences in criminal records that were not captured by the arrest records (e.g., prior jail/prison terms, juvenile system involvement, and lengthy criminal records that exceeded the 14-year pre-SVORI observation period).

3.5.2 Multilevel Logit Participation Model

This study uses propensity score techniques to balance individuals on the likelihood that they engage in employment programs (Haviland et al., 2007). Propensity score matching should address violations of two key assumptions required to compare treatment and comparison group outcomes (Heckman et al., 1997). The conditional independence assumption requires that the outcome for untreated men does not influence their participation: Men's probability of rearrest or reincarceration does not influence their selection into employment-focused programming. The overlap assumption specifies that for any value of x, $0 < Prob\left((d_1 = 1|x)\right) < 1$. At any level of x, there should be a similar mix of nonparticipants and participants in the sample, such that there is a nonparticipant who is similar to each participant in the sample (Apel & Sweeten, 2010a; Greene, 2012; Haviland et al., 2007; Heckman et al., 1997).

Defining Program Participation

The original analysis plan had included prison industry work and work release employment in the definition of program participation, based on the expectation that prison industry work and work release employment provided relevant work skills (e.g., competing treatments to vocational education/job training). Unfortunately, sample members holding work release/prison industry jobs were significantly different from the rest of the sample; they were older, more educated, serving shorter prison sentences, and were less likely to have been convicted of a violent offense (results not presented). Diagnostic tests (traditional bivariate statistics and standardized bias estimates) revealed that lingering biases resulted from the inclusion of prison industry work and work release employment in the definition of employment-focused program participation.[2]

Furthermore, half of the men holding these industry/work release jobs had not received any other educational/employment services. Defining prison industry/work release jobholders as participants, many of whom had received no other employment-focused services, led to poor matching results. The matched participants who held prison industry/work release employment remained persistently different from nonparticipants, but also from other participants. As a

[2] Pre- and post-matching standardized bias tests using this original participation definition are available upon request. Mean and median standardized biases after matching were smaller than before matching, but bivariate tests show that the matching process retained large differences between individuals who held work release/prison industry employment and the other sample members (nonparticipant and participant alike) who did not.

result, matched participants receiving the main treatments of interest (vocational education/job training) remained significantly different from the matched nonparticipant sample.

Upon realizing this problem, participation was redefined to fit the narrower criteria described in the Measures subsection of this chapter: educational services of any kind and/or vocational education/job training programs. Because roughly half of the prison industry/work-release jobholders also received some form of education or job training services, this group divided evenly among participants and nonparticipants.

Estimating the Logit Participation Model

Several logit models were fit to reduce standardized biases to an acceptable level (mean standardized bias under 5%; maximum standardized bias under 20%). These models included a 1-level logit model that included individual-level characteristics, SVORI participant status, and state dummies; a 2-level logit model, in which individuals were nested within SVORI participant status; a kitchen-sink logit model that included multiple measures for each construct (demographics, employment history, criminal history, health status, substance use, attitudinal measures); and a an expanded version of the kitchen-sink model that included squared, cubed, and interaction terms for significant predictors. These models did not effectively capture the state-level variations in participation, so they were discarded in favor of the 2-level logit model that nests individuals within SVORI sites (US states).

Fitting the Multilevel Logit Model

The multilevel logit model (Stata13 *melogit*) estimates men's predicted probability of participation in educational services, vocational education, or job training programs. Individuals were nested within state sites to control for substantial state-level variation in prisoners' demographic characteristics, criminal histories, and access to educational or employment-focused services. State SVORI site is included in the model as a level-2 random effect, and baseline demographic and risk characteristics are included in the model as level-1 covariates.

Items from the baseline interview that reflected men's pre-prison characteristics were included in the logit model, and these self-report interview items were supplemented by variables that had been created from the NCIC arrest records. Continuous covariates are included in the model after centering observations on mean values for each state. Trajectory group membership is included in the model as dummy variables and as interactions with state-centered age at release, state-centered level of education (in years), and number of previous imprisonments. These individual-level characteristics do not completely remove the state-level variation in participation status. The final multilevel logit model reveals that 16% of the variation in participation status occurred at the state level.

3.5.3 Propensity Score Matching

Steps to Assess Covariate Balance

Propensity scores that effectively remove imbalances along potential confounders satisfy the conditional independence assumption (Apel & Sweeten, 2010a). Two methods assess whether the PSM has achieved covariate balance. First, the distribution of scores within treatment and comparison groups can be compared to determine whether there is common support across levels of *x*. Insignificant differences across most to all covariates within each bin provide supporting evidence that the model has achieved covariate balance (Apel & Sweeten, 2010a).

Second, estimates of the standardized bias before and after matching can be used to compare the results derived from various matching methods. Standardized bias estimates that exceed 20 indicate covariate imbalance (Apel & Sweeten, 2010a; Rosenbaum & Rubin, 1985). To meet the overlap assumption, propensity scores for cases in each treatment condition should overlap, with few off-support cases in tails of the score distribution and ideally common support across all values between 0 and 1 (Apel & Sweeten, 2010a; Heckman et al., 1997).

Matching Estimation Techniques

Nearest neighbor matching is the simplest method, and it permits matching to single or multiple cases, with or without replacement. Matching to multiple nonparticipants reduces variance but can increase bias because some matches are less accurate. Matching without replacement works well when untreated and treated cases are located along the whole propensity score distribution. Matching with replacement permits treated cases to be matched to the same untreated cases; this can improve the quality of the matches, although it reduces the effective sample size. This loss of efficiency is preferred to the potential increase in bias that can occur when using matching without replacement (Apel & Sweeten, 2010a).

Caliper matching sets an additional parameter to the nearest neighbor matching technique; the caliper sets the maximum area from which untreated cases can be matched to treated cases. This helps ensure that matched pairs have similar propensity scores (Apel & Sweeten, 2010a). The initial caliper width proposed for use in the matching model was 0.2 of the standard deviation of the propensity score logit (Rosenbaum & Rubin, 1985).

Kernel matching techniques may be preferred in cases where untreated and treated cases are less evenly distributed. The finite probability distribution function used as a kernel weights untreated cases by their distance from the treated case. If a uniform kernel is used, this method can increase the number of untreated cases to which treated cases are matched, as it matches treated cases to all untreated cases within a given radius. The Epanechnikov kernel matches treated cases to all untreated cases located within a pre-specified bandwidth (Apel & Sweeten, 2010a).

Propensity Score Estimation Methods

The Stata user-written *psmatch2* command was used to implement various matching estimators. Matches were restricted to regions of common support. Prior to matching, the Stata user-written *pscore* command was used to divide the sample into 5 bins of equal size. The program showed that there were no significant differences between participants and nonparticipants within the same bin. The *pstest* command was used to assess standardized biases for key predictors before and after matching.

Results from multiple matching estimators were evaluated to assess which estimator produced optimal matches (Apel & Sweeten, 2010b). Nearest neighbor matching with caliper, and permitting various numbers of matches, was used as the primary matching technique. To supplement results derived from nearest neighbor matching techniques, this study implemented a second set of models that use kernel matching. Various forms of kernel matching estimators (Epanechnikov, Gaussian, tricube and uniform kernels) were considered, but these alternatives resulted in greater loss of cases without any corresponding improvement in balance.

Implementing Propensity Score Matching

The dissertation proposal initially specified that matches would be restricted to individuals within the same trajectory group (Haviland & Nagin, 2005; Haviland et al., 2007; Haviland et al., 2008). When efforts were made to restrict matching to within the same trajectory group, participants and nonparticipants in the high-rate trajectory groups (Groups 1 and 3) showed adequate balance using most matching techniques. Despite this, mean standardized biases exceeded 5% for all matching methods, and standardized biases for key predictors exceeded 10% (e.g., age at release, SVORI prison term). Matching estimators failed to achieve balance when matching individuals within the low-rate offending group (Group 2). Instead, the matching process was modified to permit matching across trajectory groups.

3.5.4 Duration Models

Duration models estimate the effect of employment programs on rearrests during the first 3 years of release (Sedgley et al., 2010). The repeated-events model estimates the time to each new arrest date that occurred within the first 3 years of release. For men with multiple recorded arrests, the time to subsequent arrests was adjusted to reflect the time that had lapsed since the preceding arrest. In the single-event duration models, respondents remain in the sample until they experience the event, at which point they are removed from the sample as failures (Zweig et al., 2011).

The duration models use parametric regression models to measure time to arrest in five different formats: time to arrest within the first 3 years with repeated events permitted, time to first arrest for any offense, and time to first arrest for three offense subtypes (drug, property, and violent offense). The Gompertz distribution provided the best fit to the data in the repeated-events failure model. To account for the dependence due to repeated observations for the same individual, standard errors use robust estimation with clustering at the individual level. In the case of the four models estimating time to first arrest, the Weibull distribution provided the best fit to the data. In these models, standard errors use robust estimation with clustering at the state level.

3.5.5 Structural Equation Modeling

Structural equation modeling (SEM) provides more flexibility than traditional regression-based approaches in modeling measurement error, time-specific parameter estimates, and cross-lagged effects (Bollen & Brand, 2010). SEM can model explicitly the measurement error that results from random noise (Bollen & Brand, 2010; Krohn et al., 2011). The Confirmatory Factor Analysis (CFA) submodel depicts relationships between the latent factor and indicators used to measure each latent factor (Bollen & Noble, 2011). The CFA measurement submodel permits use of multiple indicators of the same construct to enhance measurement accuracy (Bollen & Bauldry, 2011). It enables one to specify correlations between indicators. The CFA permits error terms for indicators to be correlated when there is a theoretical or methodological reason for the error terms to correlate (Bollen & Noble, 2011).

The structural submodel models the inter-relationships between latent factors and the observed indicators that reflect these latent constructs (Bollen & Brand, 2010; Krohn et al., 2011). Figure 2.2 presents the original proposed structural model. Figure 3.5 presents the initial longitudinal structural equation model (LSEM). Figure 4.10 presents the CFA results and Figure 4.11 presents the results of the LSEM. Ellipses represent latent constructs that were retained from the CFA. Squares and rectangles represent observed variables.

Assessing Factorial Invariance over Time

Tests were conducted to assess whether the indicators exhibited factorial invariance over time. Indicators that exhibit consistent factor loadings, intercepts, and variances over time can be said to be measuring the same construct over time, with differences over time reflecting changes in the underlying construct. To test this assumption, a series of nested models were conducted that imposed increasingly stringent requirements on model parameters. Fit statistics for each nested model were compared to the fit statistics for the preceding model to assess whether the items met the assumption of invariance at each stage. Meade, Johnson, and Braddy (2008) recommend using a change in the Comparative Fit Index (CFI) of .002 as the threshold for rejecting this assumption.

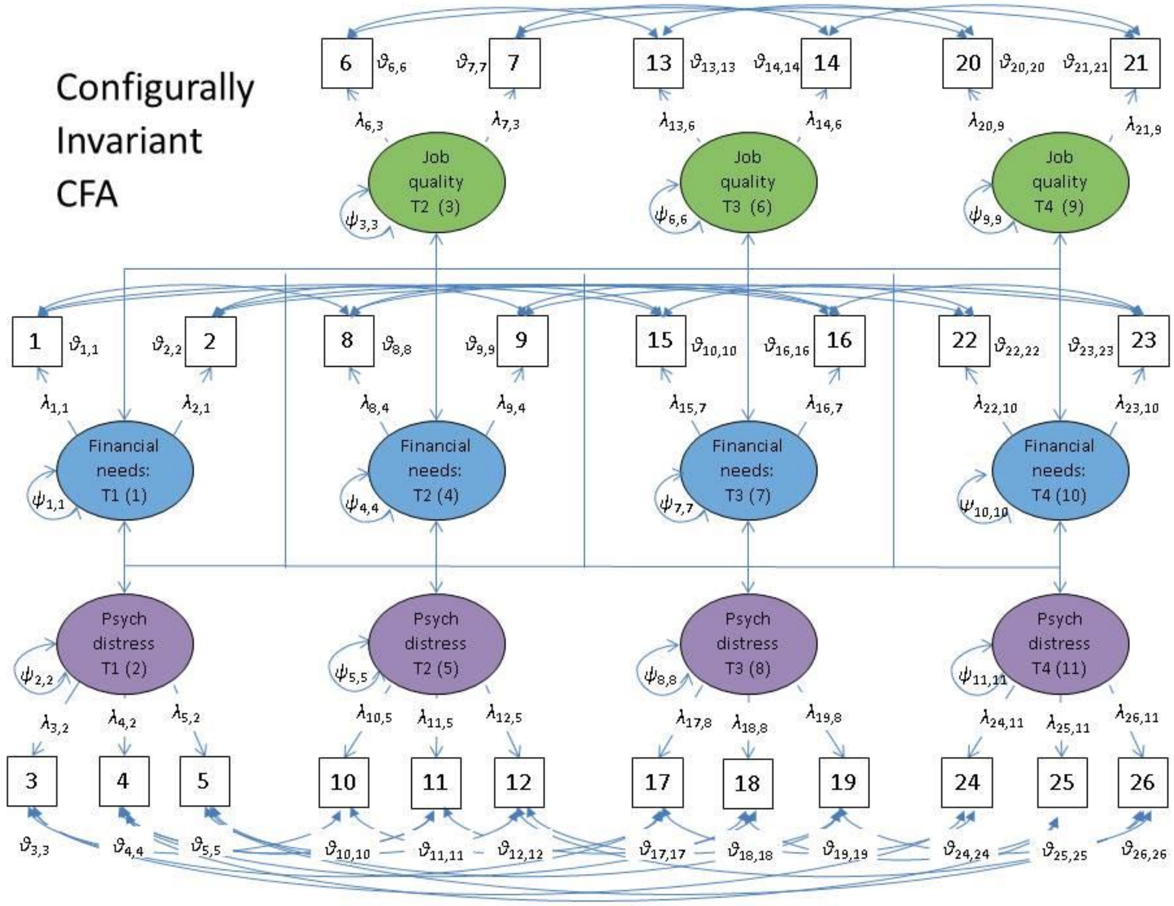


Figure 3.2 Parameter Labels for Four Time Points: The Configural Invariance Model.

The configural invariance model estimated all parameters freely, with restrictions only on the patterns of loadings on factors (Figure 3.2). The weak invariance model constrained factor loadings to equality at each time point, but intercepts and variances remain freely estimated (Figure 3.3). The strong invariance model constrained factors and loadings to be equal at each period (Figure 3.4). If the model passes the assumption of strong factorial invariance, the model can be used to examine changes in latent means over time.

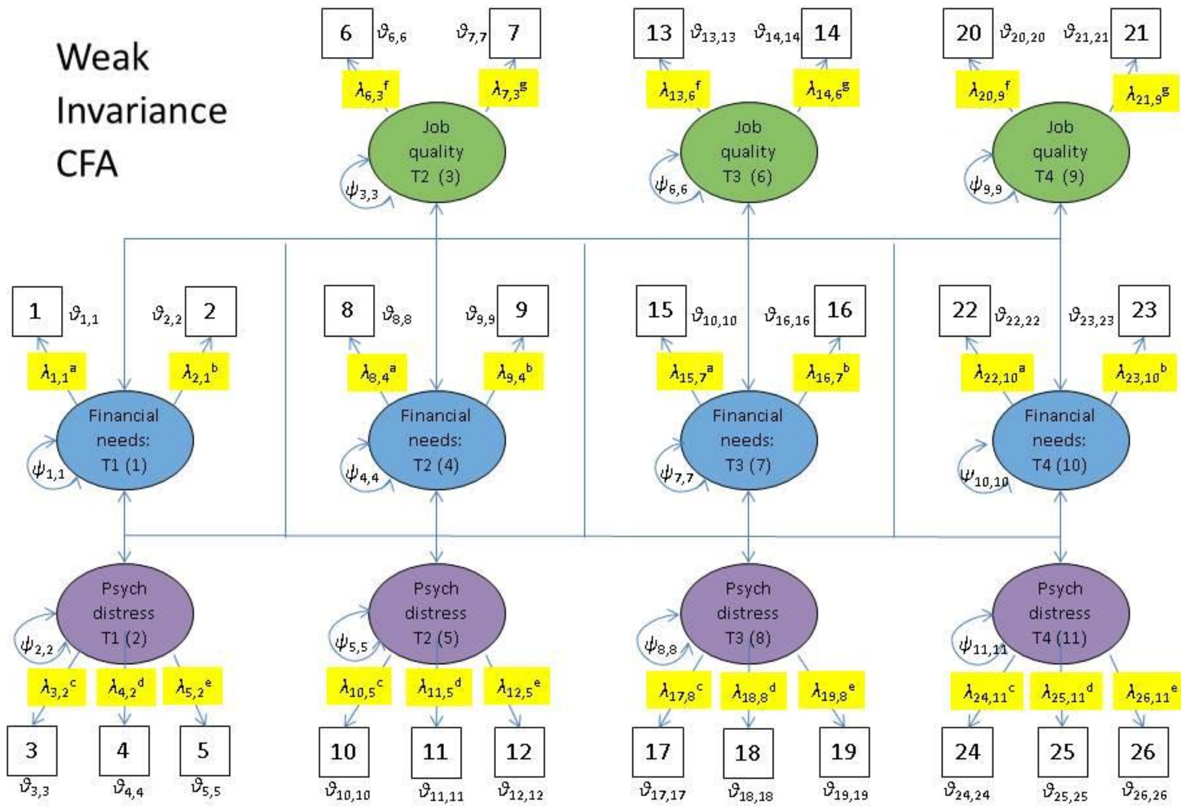


Figure 3.3 Parameter Labels for Four Time Points: The Weak Invariance Model.

Structural Equation Path Model

This study adapts the path model depicted in Thornberry & Christenson (1984). Prior criminal activity is predicted to influence men's current labor force participation and job conditions through changes in men's stock of human and social capital (Heckman et al., 2006; Sickles & Williams, 2008; Thornberry & Christenson, 1984). The path model is estimated by Mplus version 7.3, using maximum likelihood estimation with robust standard errors, because the employment, crime, and recidivism measures are binary indicators.

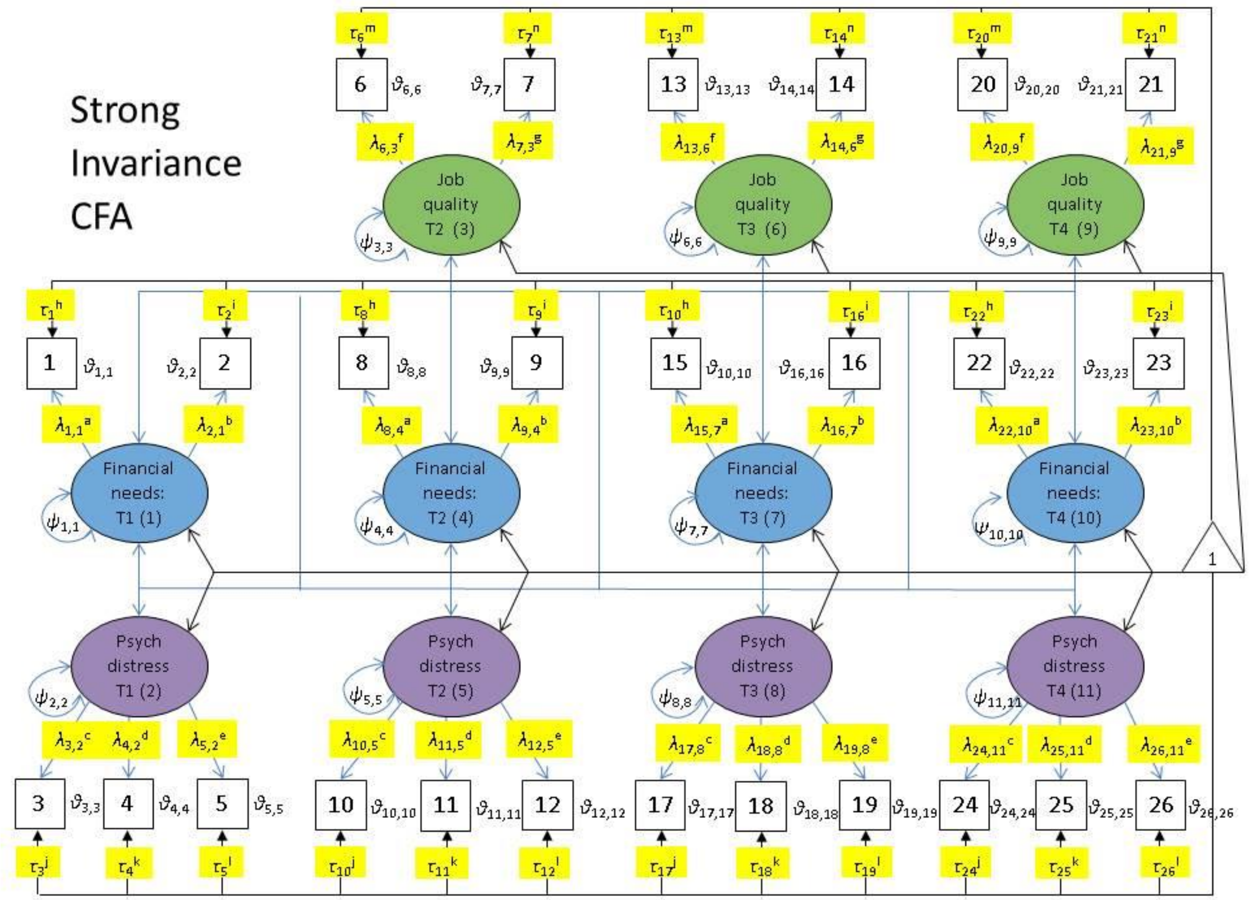


Figure 3.4 Parameter Labels for Four Time Points: The Strong Invariance Model.

Control variables were regressed on latent and observed endogenous variables from the final analysis period and on work and crime outcomes at each follow-up wave. Models' AIC values were used to compare competing non-nested models to determine which one provided the best fit to the data. The final sample size for the general structural equation model was 1,243 cases.

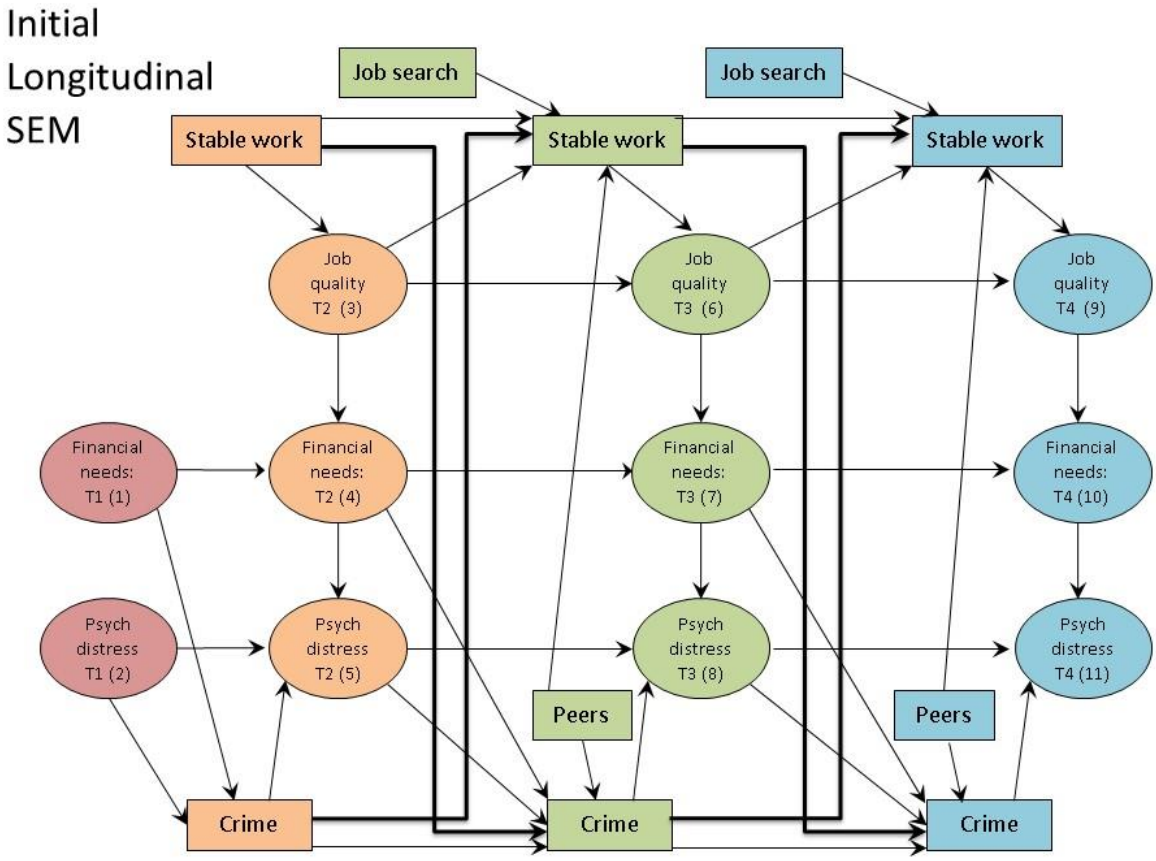


Figure 3.5 Initial Longitudinal Structural Equation Path Model.

Chapter 4: Results

4.1 Overview

This chapter presents results of the trajectory group modeling, propensity score matching, duration models, and structural equation modeling. This chapter begins by presenting descriptive characteristics of the study sample at the time of the baseline interview. This chapter next presents results of the trajectory group model, propensity score matching process, and duration models, all of which are used to test the effect of employment programs on arrest outcomes following release from prison. Information from the trajectory group model is included in the logit model used to model the probability of receiving employment-focused services. The matched sample obtained from propensity score matching is used to model time to rearrest in the repeated-event and single-event failure models.

The second half of the chapter presents results of the longitudinal structural equation model. The CFA model is tested for invariance over time, and the best-fitting model meets the assumptions of strong invariance over time. Using the strong invariant CFA model, the longitudinal SEM includes four interview waves. The best-fitting model regresses all endogenous constructs and observed variables on covariates from the baseline interview and NCIC arrest record files.

Primary outcome measures are presented at the beginning of each analysis section: pre-SVORI arrests are used to fit the group-based trajectory model, employment-focused service receipt is used in the logit participation model, several time-based rearrest measures are included in duration models, and work and crime outcomes at each follow-up interview are included in the structural equation model.

Table 4.1 Demographic Characteristics at Baseline.

	Total sample	
	N / M	% (*SD*)
Pre-SVORI criminal record (NCIC records)		
Age at first arrest (range 7-66)	19.57	(3.86)
Lifetime sum of recorded arrests (range 1-66)	8.66	(7.76)
Years since first arrest (at time of release) (range 0-52)	10.04	(6.65)
Number of years with any recorded arrest (range 1-30)	5.03	(3.49)
SVORI status offense		
Sentencing offense (percentages do not sum to 1)		
Drug offense	541	34.55
Property offense	376	24.01
Person/violent offense	644	41.12
Missing SVORI sentencing offense	9	0.57
Parole/probation violation	460	29.21
Time served, years (range 0.16-26)	2.66	(2.61)
Pre-release interview: Self-reported criminal record		
Age at first arrest (SR) (range 7-67)	16.13	(4.99)
Ever spent time in juvenile corrections facility	772	49.02
Pre-SVORI arrests (SR) (range 0-45, cap 95%)	12.41	(11.07)
Missing data	105	6.67
Prior convictions (SR) (range 0-20, cap 95%)	5.09	(4.85)
Missing data	38	2.41
Prior prison terms (SR) (range 0-5, cap 95%)	1.25	(1.44)
No previous terms	649	41.44
1 previous term	394	25.16
2 previous terms	243	15.52
3 or more previous terms	280	17.88
Pre-SVORI income: Illicit wages	691	43.87
Program participation		
Employment-focused program participation	871	55.30
Educational services alone	565	40.07
Job training/vocational education alone	79	5.61
Prison industry/work release alone	62	4.40
More than one type of program	165	10.48

Note: N = 1,575. Standard deviations appear in parentheses. NCIC = National Crime Information Center. SR = Self-report. SVORI = Serious and Violent Offender Reentry Initiative.

4.2 Descriptive Results

4.2.1 Demographic Characteristics at Baseline

Table 4.1 presents data on baseline characteristics of the sample. Men's average age at first arrest was 16 years old; by release, men were 30 years old on average and had served nearly 3 years in prison. Minorities composed 70% of the sample (55% African American, 33% White, 4% Hispanic, and 8% other). At the time of the baseline interview, 40% of men reported that they were currently married or involved in a steady relationship (*n* = 628). Sixty percent of men (*n* = 947) reported that they were fathers of minor children; and 30% of them held child support orders before entering prison (Lattimore et al., 2012; Lattimore & Visher, 2009).

Four in ten respondents left prison with less than a twelfth-grade education, having not completed the GED while incarcerated (*n* = 633). Men were more likely to have received GEDs than to have graduated from high school (29% vs. 14%), indicating the possible completion of the GED during the current (or previous) prison sentence. Two-thirds of men had been employed at some point during the 6 months leading up to prison (*n* = 1,040). Those predominantly full-time positions paid average hourly wages of $10.51 (*SD* 7.62). However, most men had not held consistent employment before prison, as 60% of men had never held a job for more than 2 years.

Table 4.2 Demographic Characteristics of Program Participants before Matching.

	Participants (*n* = 809)		**Nonparticipants** (*n* = 766)		χ^2 **/ t-test**	***p***
	N / M	% (*SD*)	N / M	% (*SD*)		
Demographic characteristics						
Age at release	27.80	(6.04)	31.50	(8.04)	10.38***	<.001
18-25 years old	322	39.80	194	25.33	98.57***	<.001
26-30 years old	259	32.01	205	26.76		
31-35 years old	166	20.52	190	24.80		
36+ years old	62	7.67	187	23.10		
Education	11.71	(2.18)	11.98	(2.11)	2.48	.013
Less than HSD	369	45.72	264	34.46	88.14***	<.001
HSD	54	6.69	174	22.72		
GED	259	32.09	197	25.72		
College attendance	125	15.49	131	17.10		
Race					12.17**	.002
African American	434	53.65	438	57.18		
White	256	31.64	259	33.81		
Hisp, multi, other, miss	119	14.71	69	9.01		
Criminal risk factors						
SVORI status offense						
Drug offense	256	31.92	285	37.30	5.01	.025
Property offense	193	24.06	183	23.95	0.00	.959
Person/violent offense	375	46.76	269	35.21	21.55***	<.001
Parole/probation violation	195	24.10	265	34.60	20.95***	<.001
Time served	3.35	(3.02)	1.94	(1.83)	-11.15***	<.001
Age at first arrest (NCIC data)	19.08	(3.37)	20.09	(4.26)	5.22***	<.001
Age at first arrest (SR)	15.45	(4.47)	16.85	(5.39)	5.59***	<.001
Years since first arrest (NCIC)	8.71	(5.44)	11.44	(7.48)	8.30***	<.001
Prior arrests count (NCIC)	6.98	(5.75)	10.43	(9.11)	9.03***	<.001
Prior arrests (SR)	11.75	(10.91)	13.11	(11.19)	2.37*	.018
Prior convictions (SR)	4.83	(4.68)	5.37	(5.02)	2.19*	.029
Prior prison terms (SR)	0.95	(1.25)	1.56	(1.56)	8.55***	<.001
No previous terms/missing	408	50.43	250	32.64	77.00***	<.001
1 previous term	197	24.35	197	25.72		
2 previous terms	102	12.61	141	18.41		
3 or more previous terms	102	12.61	178	23.23		

Table 4.2 Demographic Characteristics of Program Participants before Matching.

	Participants (*n* = 809)		**Nonparticipants** (*n* = 766)		χ^2 **/ t-test**	***p***
	N / M	% (*SD*)	N / M	% (*SD*)		
Work history						
Pre-SVORI income						
Family	278	34.49	204	26.67	11.30**	.001
Friends	133	16.50	107	13.99	1.92	.166
Government	75	9.31	83	10.85	1.04	.309
Illegal activity	391	48.51	300	39.22	13.76***	.000
Recent work before prison	511	63.16	529	69.06	6.10*	.014
Recent job: Permanency					7.05	.029
Permanent position	370	45.79	397	51.96		
Temporary employment	140	17.33	130	17.02		
Recent job: Stability					11.20**	.004
Formal pay	390	48.27	370	48.43		
Casual pay/self-employment	120	14.85	157	20.55		
Recent job: Hourly wage	9.78	(6.41)	11.21	(8.58)	2.98**	.003
Longest period at one job					44.79***	<.001
Never worked	89	11.11	54	7.09		
Less than 6 months	182	22.72	127	16.67		
6 to under 12 months	147	18.35	118	15.49		
1 to under 2 years	156	19.48	132	17.32		
2 to under 5 years	148	18.48	192	25.20		
More than 5 years	79	9.86	139	18.24		
Prior terminations (if worked)					11.04*	.026
0 times	355	49.65	301	42.45		
1 times	186	26.01	193	27.22		
2+ times	174	24.34	215	30.32		
Mental and physical health						
Pre-SVORI recent alcohol use	548	67.82	506	66.32	0.40	.526
Pre-SVORI recent drug use	563	69.59	490	64.05	5.45*	.020
Global Severity Index (GSI)	66.34	(21.47)	67.59	(23.37)	1.10	.270
Positive Symptoms Total	12.56	(9.61)	12.92	(10.29)	0.72	.468
General mental health score	49.24	(9.95)	48.40	(11.20)	-1.57	.116
General physical health score	54.42	(8.03)	52.29	(10.17)	-4.61***	<.001
Prior MH/AOD use treatment	378	46.72	424	55.50	12.10**	.001

Table 4.2 Demographic Characteristics of Program Participants before Matching.

	Participants (n = 809)		Nonparticipants (n = 766)		χ^2 / t-test	*p*
	N / M	% (*SD*)	N / M	% (*SD*)		
SVORI site characteristics						
SVORI participant status	471	58.22	330	43.08	36.08***	<.001
Probability SVORI status	52.44	(8.31)	49.45	(8.74)	-6.97***	<.001
Mandatory enrollment	201	24.85	104	13.58	32.00***	<.001
Avg. unemp. rate, 2000-2005	5.29	(0.93)	5.49	(1.04)	4.04***	<.001
SVORI site location						
Iowa	99	12.24	69	9.01	138.38***	<.001
Indiana	58	7.17	99	12.92		
Kansas	27	3.34	42	5.48		
Maryland	66	8.16	181	23.63		
Missouri	61	7.54	21	2.74		
Nevada	89	11.00	57	7.44		
Ohio	65	8.03	18	2.35		
Oklahoma	54	6.67	36	4.70		
Pennsylvania	57	7.05	59	7.70		
South Carolina	182	22.50	158	20.63		
Washington	51	6.30	26	3.39		
State civil disabilities index	4.79	(0.65)	4.82	(0.58)	1.02	.307
Driver's license	0.52	(0.38)	0.46	(0.40)	-3.28**	.001
TANF benefits	0.48	(0.32)	0.53	(0.30)	3.27**	.001
Public records	0.45	(0.19)	0.43	(0.20)	-2.23*	.026
Employment restrictions	0.71	(0.26)	0.75	(0.26)	3.00**	.003

Note: N = 1,575. Standard deviations appear in parentheses. GED = General Equivalency Diploma. HSD = High School Diploma. MH/AOD = Mental health, alcohol, or drug. NCIC = National Crime Information Center. SR = Self-report. SVORI = Serious and Violent Offender Reentry Initiative. TANF = Temporary Assistance to Needy Families.
* p < .05, ** p < .01, *** p < .001.

4.3 Assessing Initial Bias before Matching

4.3.1 Bivariate Statistics before Matching

Table 4.2 presents baseline characteristics by participation status before matching. Education and employment program participants were significantly younger than nonparticipants were (M_{part} = 27.80, SD_{part} = 6.04; M_{non} = 31.50, SD_{non} = 8.04; t = 10.38, $p < .001$) and were less likely to have completed high school (6.69% of participants vs. 22.72% of nonparticipants). Participants were also more likely than were nonparticipants to have been convicted of a violent offense (46.76% and 35.21%, respectively) and to report having recently earned income from illegal activity (48.51% vs. 39.22%). Reflecting their youth, participants were more likely to be completing their first prison term and less likely to be completing a sentence for a technical parole/probation violation. They had also acquired shorter work histories than nonparticipants had, and a higher percentage reported having received financial support from family members before entering prison (34.49% of participants, compared to 26.67% of nonparticipants).

Using data from official arrest records, participants had acquired shorter criminal records than nonparticipants had, in terms of prior arrests (M_{part} = 6.98, SD_{part} = 5.75; M_{non} = 10.43, SD_{non} = 9.11; t = 9.03, $p < .001$) and years since first arrest (M_{part} = 8.71, SD_{part} = 5.44; M_{non} = 11.44, SD_{non} = 7.48; t = 8.30, $p < .001$). Despite this, average age at first arrest was younger among participants (M_{part} = 19.08, SD_{part} = 3.37; M_{non} = 20.09, SD_{non} = 4.26; t = 5.22, $p < .001$), and they had acquired nearly the same number of convictions as nonparticipants, albeit within a shorter timeframe (M_{part} = 4.83, SD_{part} = 4.68; M_{non} = 5.37, SD_{non} = 5.02; t = 5.22, $p < .001$).

4.3.2 Hypothesis 1: Participants Differ from Nonparticipants

The first column of Table 4.5 presents standardized biases before matching across an array of demographic, criminal background, employment, and health factors. The results support the first hypothesis: mean and median standardized biases both exceeded acceptable thresholds before matching (5% mean/median bias). Key demographic and risk factors exhibited the largest biases, including age at release (52.3), sentence length (56.7), and prior prison experience (37.9). These pre-matching biases suggest that the participant group was composed of younger, higher-risk individuals; their self-report and official arrest records indicate earlier onset of criminal activity, and their young age placed them at heightened risk of reoffending following release from prison.

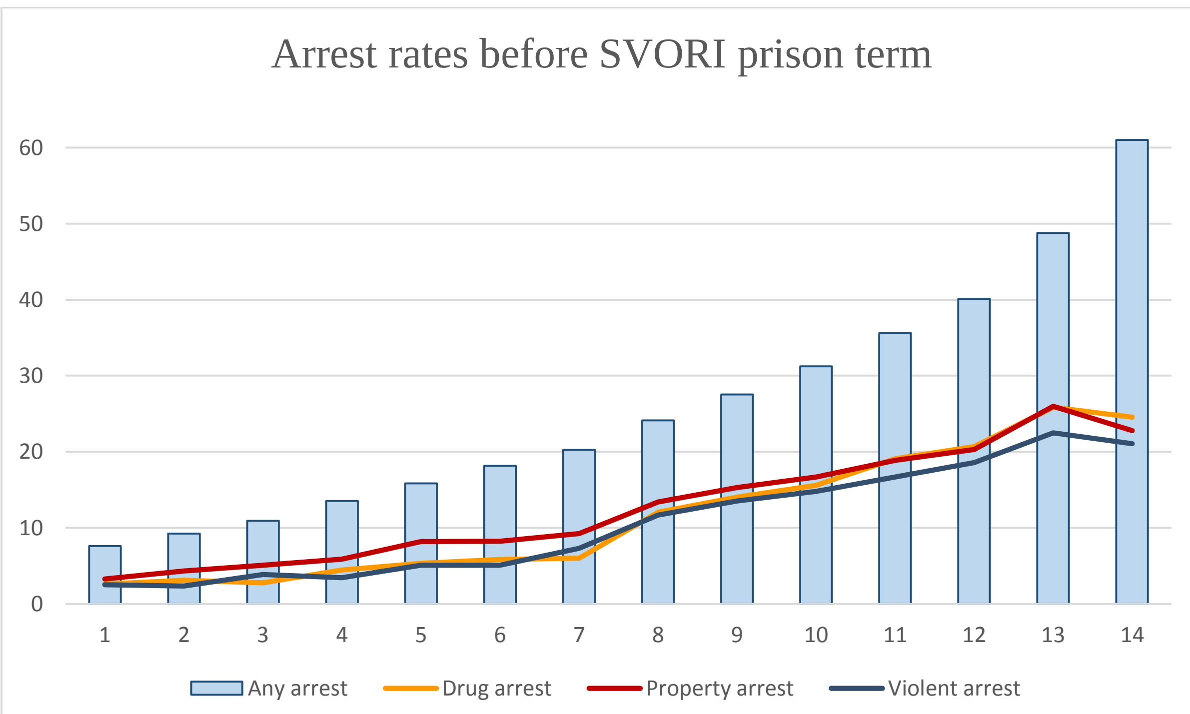


Figure 4.1 Pre-SVORI Arrest Rates by Offense Type.

4.4 Group-Based Trajectory Model

4.4.1 Pre-SVORI Arrest Rates

Figures 4.1-4.5 present arrest rates during the 14-year period preceding the start of the SVORI prison term. Arrest rates increased throughout the period, in part reflecting the rising involvement in criminal activity that led to men's eventual convictions and imprisonments, but also reflecting the relatively young ages of many sample members during the initial years of observation. Arrests by specific offense rose at approximately the same rates over time, primarily because men often received charges for multiple offenses during the same arrest. African American men were arrested at higher rates throughout the observation period. With the exception of property offenses during the final years before the SVORI term, African Americans were more likely to be charged with all offense types than were other men.

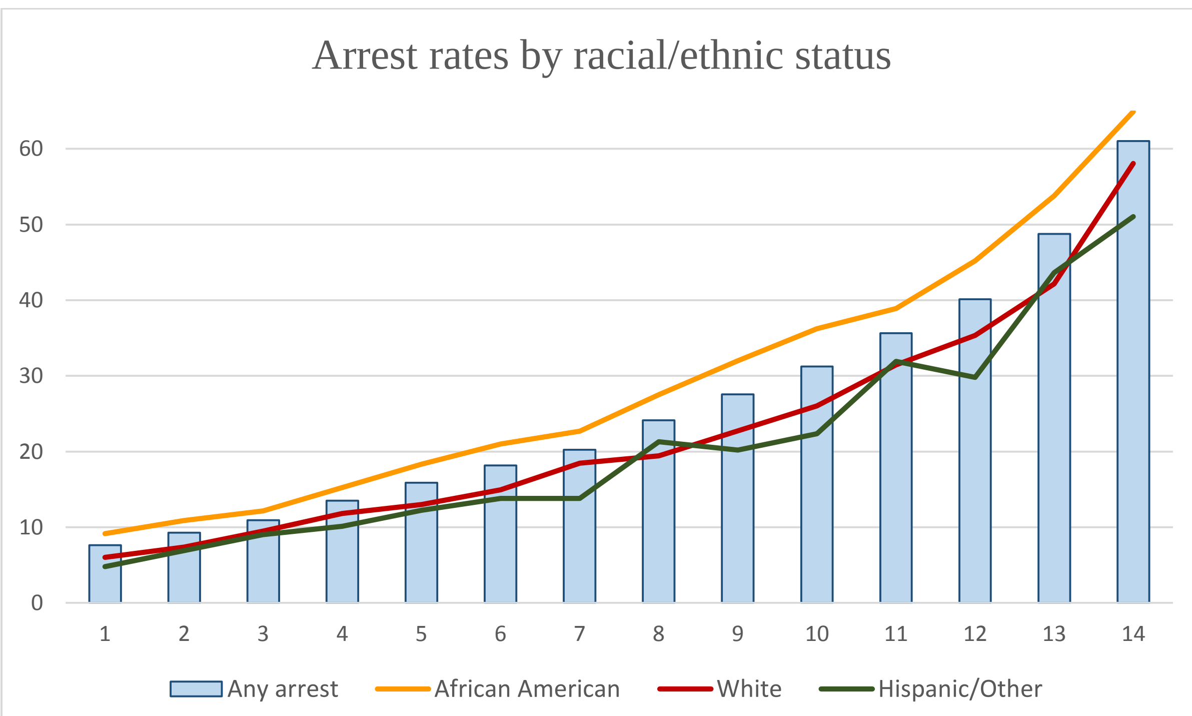


Figure 4.2 Pre-SVORI Arrest Rates by Racial/Ethnic Status.

4.4.2 Group-Based Trajectory Model Results

Table 4.3 presents results of the trajectory model (*n* = 1,575). The model derived three latent trajectory groups that appear to exhibit distinctive pre-SVORI offending trajectories and associated risk factors. Men assigned probabilistically to a given trajectory group differ significantly from men assigned to the other groups on key characteristics associated with participation status, post-release employment, and risk of recidivism. The trajectory results suggest that the SVORI sample is composed predominantly of high-rate drug and property offenders (Groups 1 and 3), with a smaller group of relatively low-rate offenders who had been convicted of violent offenses (Group 2). Figure 4.6 presents the modeled arrest trajectories for each latent trajectory group.

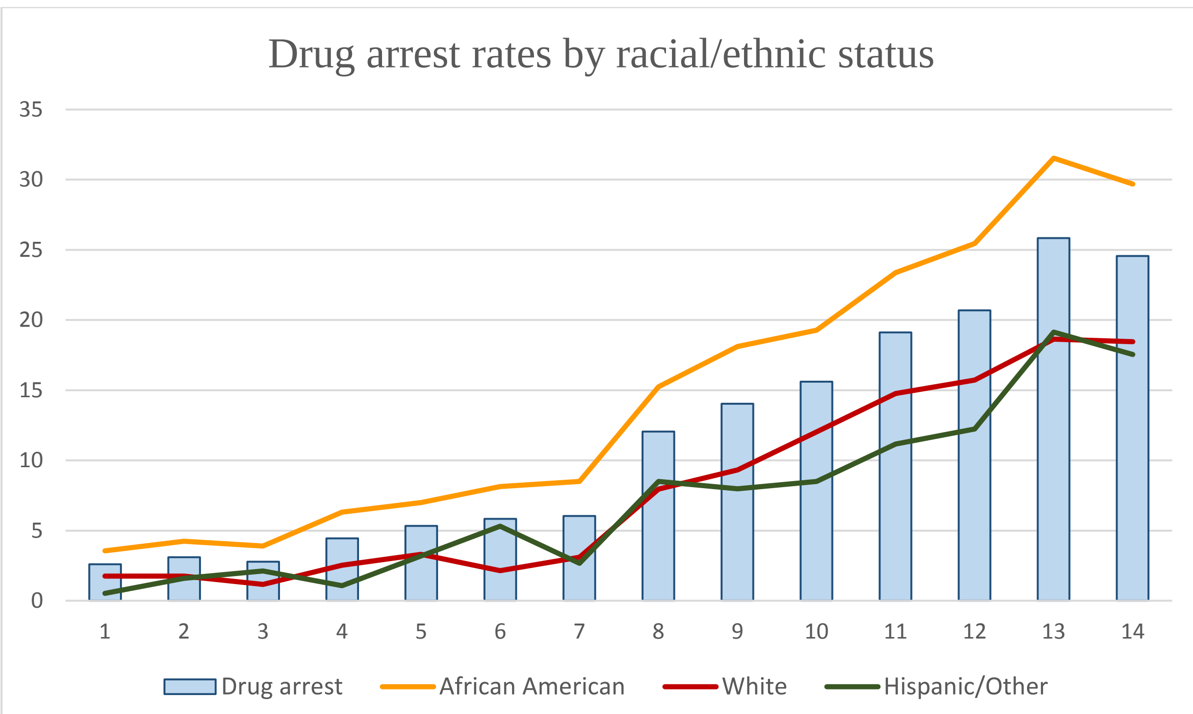


Figure 4.3 Pre-SVORI Drug Arrest Rates by Racial/Ethnic Status.

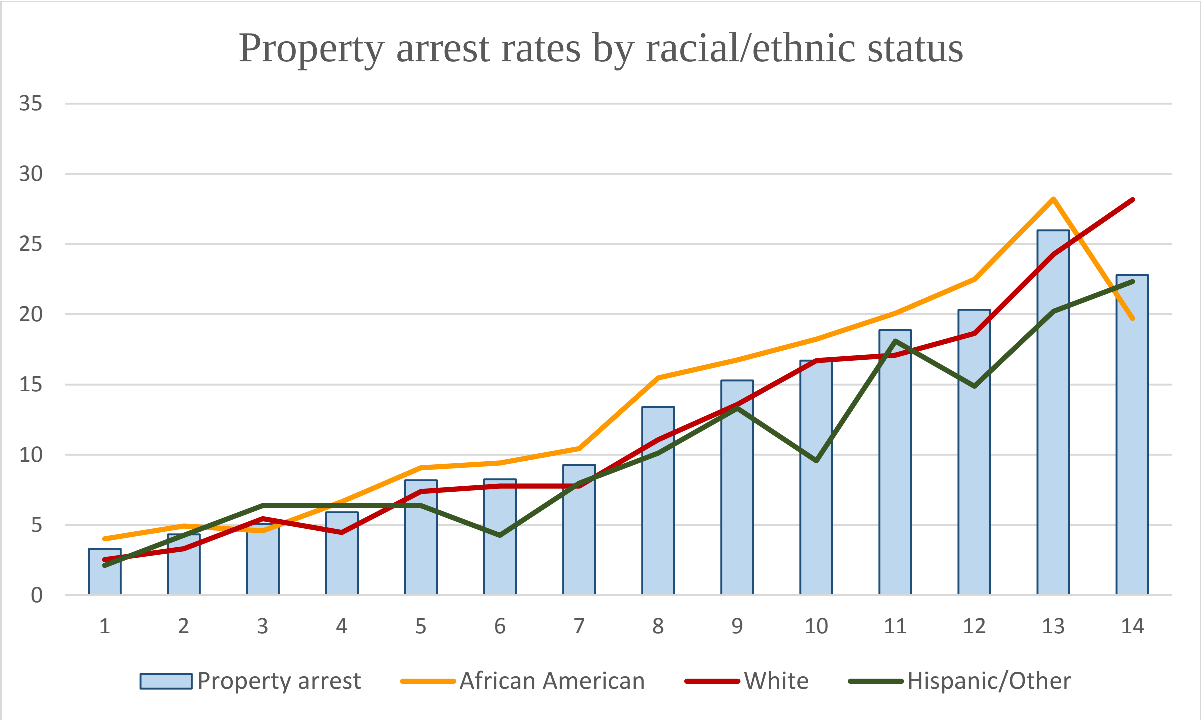


Figure 4.4 Pre-SVORI Property Arrest Rates by Racial/Ethnic Status.

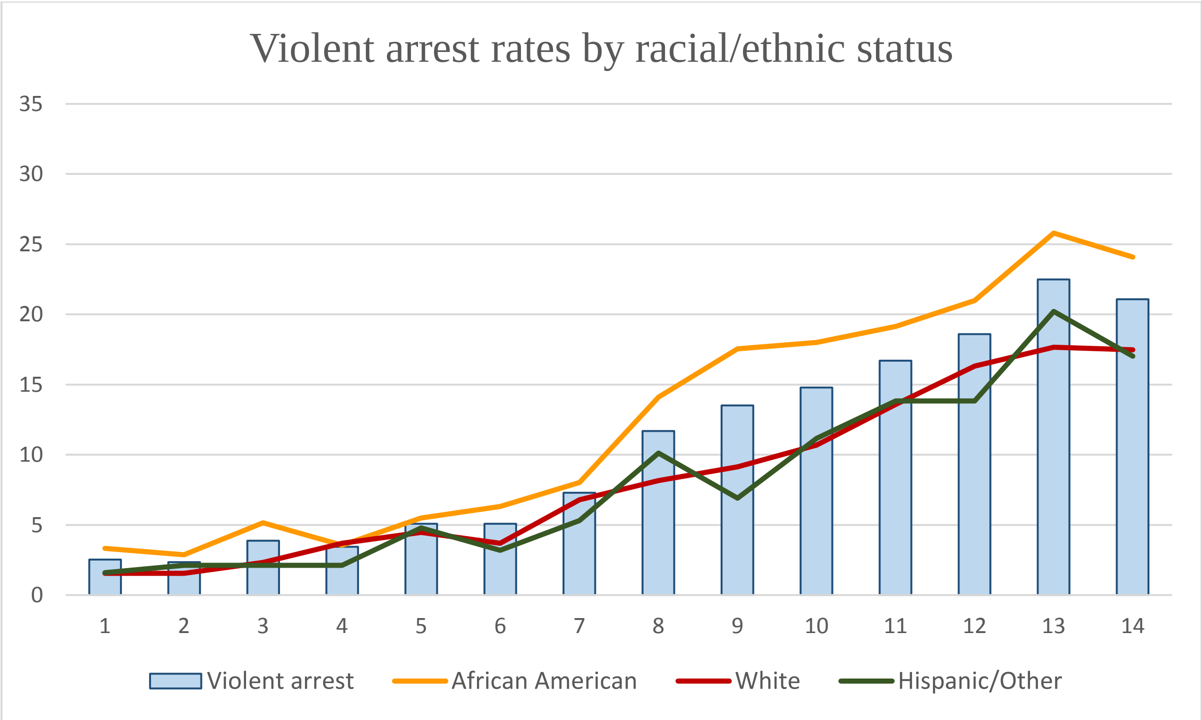


Figure 4.5 Pre-SVORI Violent Arrest Rates by Racial/Ethnic Status.

Table 4.3 Group-Based Trajectory Model Results.

	B	***se***	**t-stat.**	***P***
Logit trajectory model				
Group 1 (*n* = 864)				
Linear age at arrest	13.04***	0.69	19.00	<.001
Squared age at arrest	-0.55***	0.03	-17.75	<.001
Cubed age at arrest	0.01***	0.00	16.47	<.001
Drug arrest in prior year	0.10	0.10	1.07	.28
Property arrest in prior year	0.18	0.09	1.91	.06
Violent arrest in prior year	0.06	0.10	0.65	.52
Intercept	-101.40***	5.00	-20.27	<.001
Group 2 (*n* = 307)				
Linear age at arrest	1.80***	0.20	8.87	<.001
Squared age at arrest	-0.05***	0.01	-8.12	<.001
Cubed age at arrest	0.00***	0.00	7.47	<.001
Drug arrest in prior year	0.52*	0.23	2.29	.022
Property arrest in prior year	0.87***	0.25	3.46	<.001
Violent arrest in prior year	0.02	0.27	0.06	.949
Intercept	-21.62***	2.08	-10.38	<.001
Group 3 (*n* = 404)				
Linear age at arrest	1.14***	0.11	10.04	<.001
Squared age at arrest	-0.03***	0.00	-9.33	<.001
Cubed age at arrest	0.00***	0.00	8.54	<.001
Drug arrest in prior year	0.35***	0.08	4.29	<.001
Property arrest in prior year	0.59***	0.08	7.35	<.001
Violent arrest in prior year	0.31***	0.09	3.63	<.001
Intercept	-11.85***	1.11	-10.64	<.001
Multinomial model				
Group 2				
Age at first arrest	1.09	0.15	7.51	<.001
Number of years, any arrests	-0.44	0.23	-1.91	.056
Total lifetime arrests	-0.35	0.17	-2.02	.044
Racial/ethnic status (*ref.* AfAm)				
White	-0.11	0.39	-0.29	.775
Hisp, multi, other, miss	0.75	0.53	1.40	.161
SVORI offense: Tech. violation	0.36	0.40	0.91	.365
Prison sentence (*ref.* 3 or more)				
First prison sentence	-0.51	0.54	-0.96	.338
Second prison sentence	-0.10	0.54	-0.18	.859
Intercept	-11.85	1.11	-10.64	<.001

Table 4.3 Group-Based Trajectory Model Results.

	B	*se*	t-stat.	*p*
Group 3				
Age at first arrest	0.86***	0.18	4.86	<.001
Number of years, any arrests	3.70**	1.39	2.67	.008
Total lifetime arrests	0.23	0.15	1.52	.128
Racial/ethnic status (*ref.* AfAm)				
White	1.14	1.16	0.99	.324
Hisp, multi, other, miss	5.82*	2.71	2.15	.032
SVORI offense: Tech. violation	-5.18	2.68	-1.94	.053
Prison sentence (*ref.* 3 or more)				
First prison sentence	1.86	1.21	1.54	.123
Second prison sentence	2.02	1.26	1.61	.108
Intercept	-43.19***	12.51	-3.45	<.001

Note: N = 1,575; 20,475 obs. *se* = Standard errors. SVORI = Serious and Violent Offender Reentry Initiative. Ref. groups: Group 1, African American, Two or more previous prison terms. BIC = -8,591.96.
* $p < .05$, ** $p < .01$, *** $p < .001$.

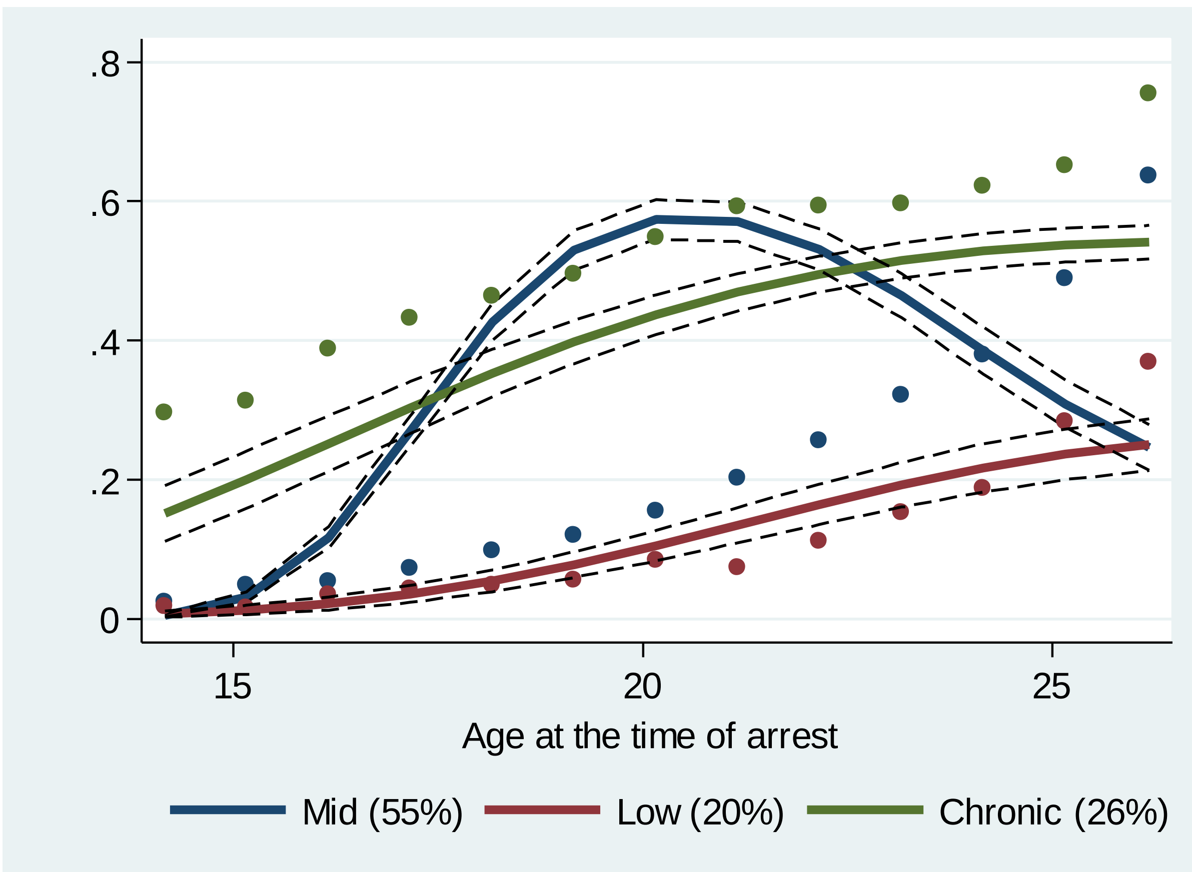


Figure 4.6 Arrest Trajectories during Years Preceding SVORI Prison Term.

4.4.3 Trajectory Group Characteristics

Table 4.4 presents bivariate statistics comparing differences by trajectory group. The results show large differences between groups for most demographic characteristics, criminal risk factors, employment history, and SVORI site characteristics. The high-rate offenders in Groups 1 and 3 differ from each other in the length of their criminal histories; men in Group 3 were chronic high-rate offenders, and their arrest records and interview responses revealed extensive criminal involvement over several years. In contrast, the men in Group 1 had only recently embarked on criminal activity; their high pre-prison arrest rates reflected escalating criminal involvement during the last few years leading up to their prison term.

Group 1

The first, largest group (n = 864) is composed of men who exhibited a relatively recent onset into criminal activity. These individuals had the highest predicted probability of being enrolled in SVORI-funded services (52.57% vs. 48.55-49.73% for the other groups). As a result, Group 1 members had the highest participation rates in education (55.09%) and employment (15.97%) programs, and men in this group exhibited many characteristics that distinguished participants from nonparticipants. Men in this group were significantly younger (M_{G1} = 26.10, SD_{G1} = 4.34) than men in groups 2 and 3 were (M_{G2} = 31.08, SD_{G2} = 7.98; M_{G3} = 35.95, SD_{G3} = 7.21; F = 382.04, $p < .001$). They were significantly more likely than were men in other groups to have received income from illegal activity before prison entry (48.84% of G1 men vs. 35.50% and 39.60% of G2 and G3 men).

Table 4.4 Demographic Characteristics of Three Trajectory Groups.

	Group 1		**Group 2**		**Group 3**		**χ^2 / *F*-test**
	N / *M*	% / *SD*	*N* / *M*	% / *SD*	*N* / *M*	% / *SD*	
	864	54.86	307	19.49	404	25.65	
Demographic characteristics							
Age	26.10	(4.34)	31.08	(7.98)	35.95	(7.21)	382.04***
Education	11.73	(2.14)	12.40	(2.10)	11.68	(2.15)	12.99***
Less than HSD	375	43.45	85	27.78	173	42.82	55.07***
HSD	93	10.78	61	19.93	74	18.32	
GED	274	31.75	85	27.78	97	24.01	
Trade/some coll.	121	14.02	75	24.51	60	14.85	
Race							63.73***
African American	495	57.29	113	36.81	264	65.35	
White	281	32.52	138	44.95	96	23.76	
Hisp/multi/other/miss	88	10.19	56	18.24	44	10.89	
Has minor child	498	58.25	170	55.74	279	69.40	18.06***
Child care/support	421	48.73	142	46.25	229	56.68	9.45**
Criminal risk factors							
Age at 1st arrest	18.14	(1.26)	23.68	(5.89)	19.52	(3.34)	331.81***
Age at 1st arrest (SR)	14.76	(3.15)	18.82	(7.46)	17.00	(4.80)	92.87***
Years since 1st arrest	7.98	(4.24)	7.41	(6.45)	16.43	(6.88)	370.21***
Years with arrests	3.81	(1.55)	2.46	(1.39)	9.58	(3.44)	1233.82***
Lifetime arrests	6.31	(3.40)	3.36	(2.14)	17.70	(9.59)	752.17***
Lifetime arrests (SR)	10.63	(10.27)	7.66	(8.64)	16.59	(12.75)	68.84***
Convictions (SR)	4.59	(4.38)	3.33	(3.73)	7.02	(5.83)	60.26***
Prev. prison (SR)	1.00	(1.22)	0.67	(1.07)	2.20	(1.65)	150.15***
First prison term	391	45.57	183	59.61	75	18.70	268.31***
Second prison term	234	27.27	79	25.73	81	20.20	
Third prison term	135	15.73	26	8.47	82	20.45	
Fourth/more term	98	11.42	19	6.19	163	40.66	
SVORI status offense							
Drug offense	293	33.91	85	27.69	163	40.35	12.56**
Property offense	229	26.50	50	16.29	97	24.01	13.02**
Violent offense	359	41.55	152	49.51	133	32.92	20.21***
Parole/probation viol.	271	31.37	93	30.29	96	23.76	7.91*
Time served	3.04	(2.85)	2.74	(2.72)	1.81	(1.58)	31.64***

Table 4.4 Demographic Characteristics of Three Trajectory Groups.

	Group 1		**Group 2**		**Group 3**		χ^2 / ***F*-test**
	N / *M*	% / *SD*	*N* / *M*	% / *SD*	*N* / *M*	% / *SD*	
	864	54.86	307	19.49	404	25.65	
Work history							
Pre-SVORI income							
Family	300	34.72	96	31.27	86	21.29	23.48***
Friends	162	18.75	36	11.73	42	10.40	18.51***
Government	67	7.75	27	8.79	64	15.84	20.59***
Illegal activity	422	48.84	109	35.50	160	39.60	20.39***
Recent work	540	62.50	235	76.55	265	65.59	19.97***
Last job: Permanency							23.96***
Permanent position	387	44.90	184	59.93	196	48.64	
Temp employment	151	17.52	51	16.61	68	16.87	
Recent job: Stability							38.79***
Formal pay	403	46.70	188	61.44	169	41.94	
Casual/self-employ	136	15.76	46	15.03	95	23.57	
Maximum job tenure							235.30***
Never worked	107	12.51	14	4.61	22	5.45	
Less than 1 year	414	48.42	74	24.34	86	21.29	
1 to under 2 years	152	17.78	58	19.08	78	19.31	
2 to under 5 years	135	15.79	95	31.25	110	27.23	
More than 5 years	47	5.50	63	20.72	108	26.73	
Job terminations							22.78**
0 times	377	50.13	122	41.78	157	41.32	
1 times	199	26.46	82	28.08	98	25.79	
2+ times	176	23.41	88	30.13	125	32.90	
Mental and physical health							
Recent alcohol use	580	67.29	195	63.52	279	69.40	2.76
Recent drug use	595	68.87	188	61.24	270	67.00	5.95+
General mental health	48.65	(10.49)	49.55	(10.02)	48.68	(11.20)	0.86
General phys. health	54.36	(7.94)	52.96	(9.39)	51.61	(11.08)	12.71***
Rec'd MH/AOD treat.	427	49.48	148	48.21	227	56.33	6.33*

Table 4.4 Demographic Characteristics of Three Trajectory Groups.

	Group 1		**Group 2**		**Group 3**		**χ^2 / *F*-test**
	N / *M*	% / *SD*	*N* / *M*	% / *SD*	*N* / *M*	% / *SD*	
	864	54.86	307	19.49	404	25.65	
SVORI site characteristics							
SVORI participant	446	51.62	163	53.09	192	47.52	2.61
Probability SVORI	52.57	(8.61)	49.73	(8.32)	48.55	(8.27)	35.26***
Mandatory enrollment	177	20.49	66	21.50	62	15.35	5.77+
Unemployment rate	5.31	(0.97)	5.13	(0.90)	5.75	(1.02)	43.19***
Recidivism rate	37.21	(0.09)	35.07	(0.08)	40.63	(0.08)	42.94***
SVORI state							236.30***
Iowa	104	12.04	37	12.05	27	6.68	
Indiana	58	6.71	47	15.31	52	12.87	
Kansas	45	5.21	10	3.26	14	3.47	
Maryland	102	11.81	18	5.86	126	31.44	
Missouri	60	6.94	9	2.93	13	3.22	
Nevada	83	9.61	48	15.64	14	3.71	
Ohio	52	6.13	7	2.28	23	5.69	
Oklahoma	54	6.25	29	9.45	7	1.73	
Pennsylvania	66	7.64	41	13.36	9	2.23	
South Carolina	205	23.73	52	16.94	83	20.54	
Washington	34	3.94	9	2.93	34	8.42	
State civil disabilities	4.80	(0.62)	5.00	(0.52)	4.66	(0.65)	26.08***
Driver's license	0.52	(0.38)	0.53	(0.35)	0.41	(0.41)	12.19***
TANF benefits	0.49	(0.31)	0.48	(0.34)	0.55	(0.27)	5.63**
Public records	0.45	(0.19)	0.47	(0.20)	0.40	(0.18)	16.32***
Employment bans	0.72	(0.26)	0.73	(0.26)	0.75	(0.25)	2.46+
Participation							
Emp-focused services	528	61.11	148	48.21	133	32.92	89.09***
Education	476	55.09	127	41.37	114	28.22	82.83***
Voc Ed/Job training	138	15.97	35	11.40	35	8.68	13.82**
Educ & Job training	114	13.2	28	9.1	23	5.7	17.26***

Note: *N* = 1, 575. Standard deviations appear in parentheses. GED = General Equivalency Diploma. HSD = High School Diploma. MH/AOD = Mental health, alcohol, or drug. NCIC = National Crime Information Center. SR = Self-report. SVORI = Serious and Violent Offender Reentry Initiative. TANF = Temporary Assistance to Needy Families.
* $p < .05$, ** $p < .01$, *** $p < .001$.

In other respects, however, men in Group 1 were not distinguishable from men in the other two groups: They shared demographic characteristics with Group 3 members (e.g., level of education, racial/ethnic status, recent work history, and rates of pre-SVORI substance use), but their criminal records more closely resembled those of men in Group 2. In many ways, Group 1 members appeared to be younger versions of men in Group 3.

Group 2

The second group obtained from the model was the smallest group of men (n = 307), and this group exhibited the most differences from groups 1 and 3. Their average age at first arrest was significantly older than for the other two groups (M_{G2} = 23.68, SD_{G2} = 5.89, compared to M = 18.14-19.52, SD = 1.26-3.34 for groups 1 and 3), and they had acquired shorter criminal histories (e.g., fewer lifetime arrests, fewer years since first arrest, and fewer years with any arrests). They were more likely to have been convicted of a violent offense than men in the other two groups were (49.51% vs. 32.92% and 41.55% of men in groups 3 and 1, respectively).

On average, these men were returning to communities in states with lower recidivism rates than men in the other two groups were (based on 2004 state recidivism rates) (M_{G2} = 35.07%; M_{G1} = 37.21%; M_{G3} = 40.63%). They also showed the strongest engagement in primary sector employment prior to entering prison. Men in this group had completed the highest levels of education (M_{G2} = 12.40, SD_{G2} = 2.10, compared to M = 11.68-11.73, SD = 2.14-2.15 for groups 1 and 3), and they were significantly less likely to be African American than men in the other two groups were (36.81% of G2 men, vs. 57.29% of G1 men and 65.35% of G3 men). They reported the highest rates of employment during the months leading up to their prison sentence, and most of the jobs had been permanent positions with benefits (76.55% of G2 men had worked recently, compared to less than two-thirds for the other two groups).

Group 3

The third group included chronic offenders who had acquired lengthy criminal records during the years preceding the SVORI status offense (n = 404). Longer time had passed on average since first arrest among Group 3 members (M_{G3} = 16.43, SD_{G3}= 6.88), relative to men in the other groups (M_{G1} = 7.98, SD_{G1} = 4.24; M_{G2} = 7.41, SD_{G2} = 6.45; F = 370.21, $p < .001$). At the time of the baseline interview, they were the oldest group on average (M_{G3} = 35.95, SD_{G3} = 7.21), and they had acquired the most lifetime arrests (M_{G3} = 17.70, SD_{G3} = 9.59). They also had the lowest average level of education, with most indicating that they had completed fewer than 12 years of education. On average, they had been imprisoned more times in the past than the men in the other two groups had been, but technical violations of previous supervision did not explain their recent return to prison (23.76% of G3 men had violated parole or probation requirements before entering prison, in contrast to 31% of G1 and G2 men). These chronic offenders were more likely to come from Maryland or South Carolina than from other states, and in general, they were returning to states with higher mean recidivism rates than were men in the other groups (2004 rates).

Summary of Findings

Based on observed characteristics, men in Groups 1 and 3 exhibited more risk factors than did the men in Group 2. The men in Group 3 had longer criminal records then men in Group 1, and they could be described as chronic adult offenders who would be likely to remain engaged in persistent criminal activity upon release. However, men in Group 1 were younger, more active offenders, and their escalating rates of arrest before prison entry suggested the possibility of more serious criminal activity upon release.

Men in Group 1 differed sharply from men in Group 3 in the likelihood of receiving employment-focused services. Most Group 1 men received some form of employment-focused programming, in contrast to men in the other two groups. Despite low educational attainment and weak attachment to primary sector employment, men in Group 3 reported the lowest rates of program participation.

The distinct compositions of the three trajectory groups may reflect the fact that prisons involved in the SVORI evaluation used differing selection criteria when recruiting participants into the study. There is evidence to suggest that the 3-group trajectory model diminished some of the pre-existing differences between employment-focused program participants and nonparticipants (reducing mean standardized bias to 10%). Despite this, participants in all three trajectory groups continued to exhibit significant differences from nonparticipants, so propensity score matching is used to reduce lingering observed heterogeneity.

4.5 Propensity Score Matching

4.5.1 Multilevel Logit Model Results

Table 4.5 presents results of the multilevel logit model (*n* = 1,571). Individuals' propensity scores were calculated from the fitted (expected) value of this logit regression, which estimated the probability of program participation based on the fixed- and random-level effects. The resulting propensity score ranges from .02 to .98, with a mean of .64 for participants and .38 for nonparticipants.

Table 4.5 Logit Participation Model Results.

	OR	*se*	*z*-stat.	*p*
Trajectory Group (*ref.* Group 1)				
Group 2	0.60*	0.13	-2.42	.015
Group 3	0.58*	0.15	-2.09	.036
Linear age at release[a]	0.93***	0.02	-3.91	<.001
Traj. Group*Age at release				
Group 2*Age at release[a]	1.04	0.03	1.71	.088
Group 3*Age at release[a]	1.02	0.03	0.70	.485
Education[a]	0.92*	0.04	-2.01	.044
Traj. Group*Education				
Group 2*Education[a]	0.97	0.08	-0.36	.722
Group 3*Education[a]	0.86*	0.06	-2.12	.034
Racial/ethnic status (*ref.* AfAm)				
White	1.10	0.16	0.66	.509
Hisp, multi, other, miss	1.62*	0.33	2.37	.018
SVORI term: Drug offense	0.92	0.17	-0.44	.662
SVORI term: Property offense	0.96	0.17	-0.23	.816
SVORI term: Violent offense	0.70*	0.12	-2.07	.038
SVORI term: Ln time served[a]	3.62***	0.49	9.50	<.001
Number of prior prison terms	0.79**	0.06	-3.39	.001
Traj. Group*Prior prison terms				
Group 2*Prison terms	1.28	0.19	1.66	.097
Group 3*Prison terms	1.27*	0.13	2.30	.022
Drug arrest, year pre-SVORI	0.83	0.14	-1.06	.289
Property arrest, year pre-SVORI	0.74	0.12	-1.92	.054
Violent arrest, year pre-SVORI	1.45*	0.22	2.42	.015
Sum arrests, year pre-SVORI	1.16*	0.08	2.08	.038
Pre-SVORI income: Family	1.35*	0.18	2.20	.028
Health limits (*ref.* None)				
Limits activities a little	0.62**	0.11	-2.74	.006
Limits activities a lot	0.55**	0.13	-2.62	.009
General physical health status	0.91*	0.04	-2.27	.023
SVORI participant	1.71**	0.21	4.40	<.001
Intercept	1.59	0.56	1.31	.189
State-level variation	0.62	0.29		

Note: N = 1,571, 11 groups (SVORI states). Level 2: ICC = 0.16 (0.06), LR = 93.72, p <.001. Level 1: Mean-Variance adaptive Gauss-Hermite integration, 7 integration points. Wald $\chi^2_{(26)}$ = 241.02, Log likelihood = -876.02, BIC = 1,958.12. SVORI = Serious and Violent Offender Reentry Initiative. Ref. groups: Group 1, African American, No health limitations. "a" indicates continuous variables centered on state means.
* p < .05, ** p < .01, *** p < .001.

4.5.2 Nearest Neighbor Matching with Caliper

Participants and nonparticipants were matched on their predicted probability of employment-focused program participation using nearest neighbor matching with caliper. The caliper size used was 0.1 times the standard deviation of the propensity score obtained from the multilevel logit model. Replacement was permitted and up to five matches were permitted, although the results were unchanged when fewer matches were permitted.

Nearest neighbor matching with caliper successfully reduced mean standardized biases to below 5%. Forty nonparticipants were excluded from the final sample, due to the inability to find appropriate matches within the participant sample (34 nonparticipants from Group 3, 4 from Group 1, and 2 nonparticipants from Group 2). The final sample consisted of 805 participants and 726 nonparticipants (n = 1,531). Figure 3.1 presents the sample selection process used to identify trajectory groups, model participation status, and match participants and nonparticipants.

4.5.3 Bivariate Statistics after Matching

Table 4.6 presents pre- and post-matching standardized biases for key predictors of participation and post-release rearrest. The nearest neighbor matching process eliminated much of the observed bias. Mean standardized bias declined from 19.1 to 3.8, and the maximum standardized bias for individual items declined from 56.7 to 18.2. Most importantly, standardized bias for linear age at release declined from -52.3 to -1.7, and bias for time served, which had exhibited the largest bias before matching, declined from 56.7 to 2.0. Other variables that exhibited large reductions in imbalance include age at first arrest (from -26.3 to -0.3), years since first arrest (-41.8 to -2.2), lifetime number of arrests (-45.6 to -3.7), and trajectory group membership (44.1 to -0.3 among Group 1 members; -44.4 to 0.3 among Group 3 members).

Table 4.6 Demographic Characteristics of Program Participants after Matching.

	Pre. SB	**Post. SB**	**Non.** (*n* = 726)	**Part.** (*n* = 805)	**Educ.** (*n* = 714)	**Emp.** (*n* = 207)
Demographics						
Linear age at release	**-52.3**	-1.7	27.91 (0.30)	27.79 (0.21)	27.58 (0.22)	27.92 (0.39)
State-centered	**-37.2**	-2.1				
18-25 years old	**31.4**	-2.8	41.17	39.88	41.32	40.58
26-30 years old	11.4	-0.5	32.17	31.93	31.79	29.47
31-35 years old	-10.0	0.1	20.59	20.62	20.31	20.77
36+ years old	**-44.1**	4.3	6.07	7.58	6.58	9.18
Education, years	-12.3	0.5	11.71 (0.12)	11.72 (0.08)	11.59 (8.08)	12.51*** (0.14)
State-centered	-18.5	-0.5				
Race						
African American	-7.3	1.1	52.99	53.54	54.48	52.17
White	-4.3	1.1	31.28	31.80	30.53	33.82
Hisp, multi, other, miss	17.6	-3.3	15.73	14.66	14.99	14.01
Criminal history						
SVORI sentencing offense						
Drug	-11.9	-1.3	32.18	31.55	30.53	36.71
Property	-0.1	0.3	23.74	23.85	23.25	25.12
Person/violent	**23.5**	-1.5	47.30	46.58	47.48	44.93
Violation	**-23.5**	-7.0	27.16	23.98	23.81	20.77
SVORI: Time served	**56.7**	2.0	3.31 (0.18)	3.36 (0.11)	3.46 (0.12)	3.08 (0.17)
State-centered	**56.3**	-1.7				
Age at first arrest	**-26.3**	-0.3	19.09 (0.16)	19.08 (0.12)	18.90 (0.11)	19.42 (0.27)
State-centered	**-21.0**	0.3				
Age at first arrest (SR)	**-28.4**	-2.4	15.56 (0.28)	15.44 (0.16)	15.21 (0.15)	16.00 (0.36)
State-centered	**-21.1**	-0.4				
Years since first arrest	**-41.8**	-2.2	8.85 (0.29)	8.71 (0.19)	8.68 (0.20)	8.50 (0.33)
State-centered	**-27.7**	-2.9				

Table 4.6 Demographic Characteristics of Program Participants after Matching.

	Pre. SB	Post. SB	Non. (*n* = 726)	Part. (*n* = 805)	Educ. (*n* = 714)	Emp. (*n* = 207)
Criminal history						
Lifetime arrests	**-45.6**	-3.7	7.24 (0.27)	6.96 (0.20)	6.93 (0.22)	6.76 (0.35)
State-centered	**-33.3**	-6.9				
Lifetime arrests (SR)	-9.4	11.1	9.85 (0.57)	11.09 (0.39)	10.99 (0.41)	10.77 (0.74)
State-centered	-7.6	8.7				
Prior convictions (SR)	-10.3	5.3	4.47 (0.24)	4.73 (0.17)	4.68 (0.17)	4.72 (0.31)
State-centered	-11.8	2.9				
Prior prison terms (SR)						
No previous terms	**37.9**	-2.7	51.51	50.18	51.54	48.31
1 previous term	-3.2	1.7	23.59	24.35	24.23	21.26
2 previous terms	-15.9	-4.5	14.31	12.67	11.62	14.98
3 or more terms	**-28.5**	6.6	9.92	12.42	12.18	15.46
Trajectory group						
Young rising	**44.1**	-0.3	65.48	65.34	66.53	66.18
Low rising	-6.3	0.1	18.24	18.26	17.65	16.91
High chronic	**-44.4**	0.3	16.29	16.40	15.83	16.91
Work history						
Income: Family	16.7	6.8	31.15	34.29	35.01	35.75
Income: Friends	6.8	-2.8	17.41	16.40	17.09	17.87
Income: Government	-5.5	6.5	7.25	9.19	9.80	8.70
Income: Illegal activity	18.5	3.5	46.59	48.32	47.06	51.21
Recent work	-12.1	-7.4	66.87	63.35	62.46	68.12
Last job: Permanency						
Permanent position	-12.0	-6.4	49.02	45.84	45.80	50.72
Temp. employment	1.1	-1.0	17.76	17.39	16.53	17.39
Last job: Stability						
Formal pay	0.0	-2.8	49.74	48.32	48.60	51.21
Casual/self-employ	-14.7	-5.1	16.86	14.91	13.73	16.91
Longest period worked						
Never worked	13.6	1.2	10.58	10.93	11.76	7.73
Less than 12 months	18.3	-2.0	41.71	40.75	42.44	34.30*
1 to under 2 years	5.2	11.1	14.97	19.25	18.35	25.60**
2 to under 5 years	-16.2	-7.9	21.62	18.39	17.23	21.26
More than 5 years	**-24.6**	-0.3	9.78	9.69	9.24	10.14

Table 4.6 Demographic Characteristics of Program Participants after Matching.

	Pre. SB	**Post. SB**	**Non.** (n = 726)	**Part.** (n = 805)	**Educ.** (n = 714)	**Emp.** (n = 207)
Health/substance use						
Recent alcohol use	3.9	7.8	64.49	68.16	67.32	69.08
Recent drug use	12.0	18.2	61.11	69.69*	69.61*	67.63
Mental health score	8.3	3.2	48.93 (0.78)	49.27 (0.35)	49.19 (0.38)	50.16 (0.62)
Physical health score	**23.2**	1.4	54.29 (0.45)	54.41 (0.28)	54.39 (0.31)	54.50 (0.53)
SVORI participation						
SVORI participant	**30.7**	0.3	58.11	58.26	56.58	75.36***
Probability SVORI	**35.5**	-2.1	52.65	52.48	52.66	53.13
SVORI site						
Mandatory enroll	**28.9**	7.1	22.07	24.84	25.49	22.22
Avg. unemp. rate, 2000-2005	**-20.5**	-4.7	5.33 (0.05)	5.29 (0.03)	5.32 (0.03)	4.98*** (0.07)
SVORI site location						
Iowa	10.7	4.8	10.83	12.30	10.22	29.47***
Indiana	-19.1	2.6	6.43	7.20	7.84	3.86*
Kansas	-10.4	3.3	2.67	3.35	3.64	2.90
Maryland	**-43.6**	1.2	7.63	8.07	8.40	6.28
Missouri	**21.5**	2.2	6.97	7.45	7.84	3.86
Nevada	12.5	0.0	11.05	11.06	11.06	14.49
Ohio	**26.0**	1.3	7.79	8.07	7.98	6.76
Oklahoma	8.2	-1.2	5.31	6.58	6.30	6.28
Pennsylvania	-2.4	-11.6	10.11	7.08	7.70	5.31
South Carolina	4.5	-7.6	25.62	22.48	22.41	16.91**
Washington	13.7	10.7	4.05	6.34	6.58	3.86
State civil disab. index	-5.2	-6.4	4.83 (0.04)	4.79 (0.02)	4.78 (0.02)	4.92* (0.04)
Driver’s license	16.6	-9.0	0.56	0.52	0.51	0.52
TANF benefits	-16.5	8.1	0.46	0.48	0.49	0.46
Public records	11.4	-1.8	0.45	0.45	0.45	0.45
Work restrictions	-15.2	1.6	0.71	0.71	0.70	0.80***
Mean standardized bias	19.1	3.8				
Med. standardized bias	15.9	2.7				
Max. standardized bias	56.7	18.2				

Note: N = 1,531. Standard errors appear in parentheses. Estimates generated using weights obtained from nearest neighbor matching. NCIC = National Crime Information Center. SR = Self-report. SVORI = Serious and Violent Offender Reentry Initiative. TANF = Temporary Assistance to Needy Families.
* $p < .05$, ** $p < .01$, *** $p < .001$.

The matching process did not eliminate all pre-matching differences, however. Four variables exhibited lingering imbalance, with bias statistics that exceeded 10.0 after matching: These were a dummy variable for longest job tenure before prison (11.1), the dummy variable for Washington State (10.7), self-reported number of lifetime arrests (11.1), and self-reported drug use during the month preceding prison entry (18.2).

4.6 Duration Models

4.6.1 Post-Release Arrest Rates

Rearrest rates among men in the SVORI sample closely resembled rearrest rates that have been observed for state prison populations as a whole (Durose et al., 2014). Three-quarters of the men were arrested at least once during the first 3 years of release (n = 1,129; 74%). On average, these men were arrested 2.96 times (SD = 2.46). Thirty-five percent were arrested at least once for a drug offense, 32% had one or more property arrests, and 28% were arrested for violent offenses. Men were frequently charged with more than one type of offense during a single arrest, so these percentages are not mutually exclusive.

4.6.2 Employment Programs Increase Labor Force Participation

Table 4.10 presents post-release labor force activity by participation status. The results suggest that employment-focused programs do have beneficial effects on employment, although results do not persist over time. Men who participated in vocational education/job training programs were significantly more likely to seek work during the first 9 months of release from prison than were nonparticipants and participants receiving educational services alone. Enrollees in vocational education/job training programs exhibited the lowest rates of labor force exit at the first two follow-up interviews. Employment program participants also exhibited the highest rates of stable employment (measured as having worked each month that they were living in the community).

In contrast, men who received educational services alone exhibited similar rates of employment as nonparticipants. Education participants were less likely to enter the labor force to seek work than were employment program participants (13.75% vs. 5.00% at Wave 2; 15.88% vs. 11.29% at Wave 3). Approximately the same proportion of education program participants held stable employment during the first 3 months, as did nonparticipants (roughly 30% of each group). By the time of the third interview (approximately 9 months after release), rates of labor force entry and employment declined among employment participants, although they remained significantly higher than for nonparticipants and education participants. By the time of the fourth interview (approximately 15 months after release), there were no significant differences in labor force activity by participation status.

4.6.3 Hypothesis 2: Employment Programs Reduce Recidivism

Findings provide limited support for the second hypothesis. Table 4.7 presents rearrest rates by participation status during the first 3 years of release. The weighted percentages reflect the proportion of each group within the matched sample who had been arrested at least once within the given reference period. During the first 9 months of release, education and employment program participants had significantly lower rates of rearrest than nonparticipants did. Participants receiving vocational education/job training programs alone were least likely to have been rearrested within that time (34.07%), compared to participants receiving education and employment services (38.79%), participants receiving educational services alone (41.30%), and nonparticipants (43.80%). These differences dwindled over time; by 1 year after release, the proportions of men within each group who had been rearrested were no longer significantly different from each other. There were also no differences in average number of arrests.

Table 4.7 Post-Release Arrest Rates by Participant Status.

	Non Part. (n = 722)	**Educ. Part.** (n = 593)	**Emp. Part.** (n = 90)	**Educ. & Emp.** (n = 116)	F	p
% with first arrest within[a]						
3 months	19.39	14.67	12.22	15.52	13.69***	<.001
6 months	32.69	28.16	21.11	30.17	11.94**	.001
9 months	43.91	41.32	33.33	38.79	8.05**	.005
12 months	50.28	48.57	45.56	49.14	1.62	.204
15 months	56.23	54.81	50.00	56.90	2.61	.107
21 months	65.10	63.74	60.00	65.52	1.88	.171
24 months (n = 1,486)	69.73	69.10	64.04	68.42	2.35	.126
36 months (n = 427)	78.44	78.95	77.27	77.14	0.14	.709
Number of arrests[b]	1.95 (0.12)	2.13 (0.09)	1.84 (0.21)	1.94 (0.20)	0.63	.427

Note: N = 1,521. Standard errors in parentheses. Estimates generated using weights obtained from nearest neighbor matching. "a" indicates rearrest items created for the original SVORI evaluation. "b" indicates rearrest items created from NCIC arrest record files for this study. Design-based F statistic based on weighted data. NCIC = National Crime Information Center. SVORI = Serious and Violent Offender Reentry Initiative.
* $p < .05$, ** $p < .01$, *** $p < .001$.

4.6.4 Duration Model Results

Repeated-Event Failure Models

Results of the repeated-events duration model are consistent with the bivariate findings. Results of the repeated events model are presented as nested findings in Table 4.8 to indicate changes in parameter estimates as additional variables are included. When controlling for group trajectory membership and probability of participation, engagement in either education or employment programs was not associated with time to rearrest. As additional variables were introduced into the model, education and employment program participation both remained unassociated with time to rearrest (education: HR = 1.15, p = .201; employment: HR = 1.06, p = .483).

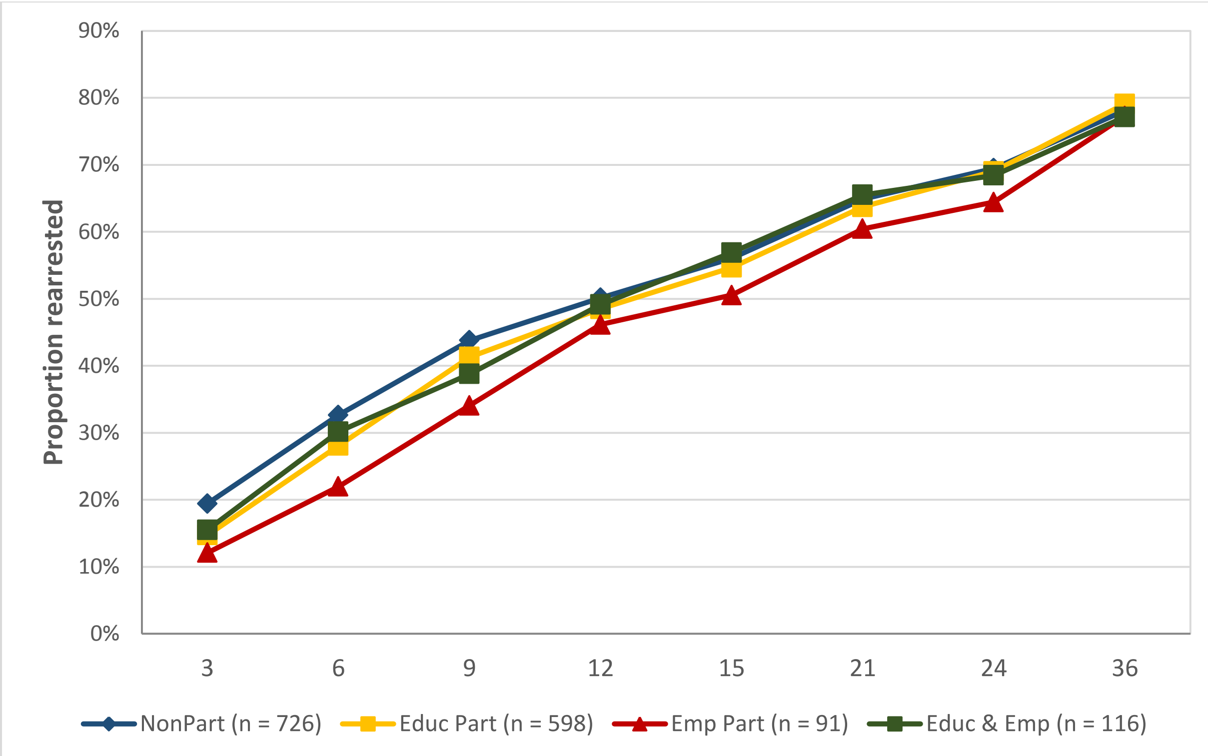


Figure 4.7 Rearrest Rates by Participation Status after Release from SVORI Prison Term.

In the full model, significant predictors include criminal risk factors, previous work experience, previous alcohol/drug use, racial/ethnic status, and state location. Past criminal involvement significantly increased the likelihood that men would be arrested at least once following release. Each additional arrest during the last year before men entered prison to complete the SVORI sentence was associated with a 9% increase in the baseline hazard of rearrest (HR = 1.09, p < .001). Property convictions and previous technical violations reduced the length of time that men remained in the community before rearrest: Property convictions increased the baseline hazard by 27% (HR = 1.27, p = .009), and men who had violated parole or probation before entering prison on the SVORI status offense had a 30% increase in the baseline hazard (HR = 1.30, p < .001). Substance use before the SVORI term also increased men's relative risk of rearrest by 22% (*HR* = 1.22, *p* = .030). When controlling for other factors, the relative risk of rearrest remained 45% larger among men in Group 3 (*HR* = 1.45, *p* = .044, *ref*. Group 1).

Table 4.8 Duration Model: Nested Results for Time to Arrest with Repeated Failures.

	HR	*HR*	*HR*	*HR*	*HR*	*HR*	*HR*
Educ programs	1.04	1.04	1.00	1.09	1.09	1.13	1.15
Voc/job training	0.91	0.92	0.99	1.00	1.01	1.02	1.06
Prob. of participation	0.72						
Group 1 Nonpart.		0.58	0.53	0.88	0.95	1.00	1.81
Group 1 Part.		**0.58****	**0.54****	0.77	0.81	0.79	1.35
Group 2 Nonpart.		0.86	0.63	0.89	0.77	0.81	0.96
Group 2 Part.		1.09	0.80	0.93	0.84	0.85	0.90
Group 3 Nonpart.		1.04	0.60	0.90	0.91	0.89	1.62
Group 3 Part.		0.99	**0.58***	0.68	0.71	0.67	1.06
Trajectory group (*ref*. Group 1)							
Group 2	**0.54*****	**0.39****	**0.54***	0.75	0.83	0.82	1.18
Group 3	**1.28****	0.94	1.42	1.40	**1.46***	**1.48***	**1.45***
Age at release[a]			**0.97*****	**0.97*****	0.98	0.98	0.99
Education[a]			**0.93*****	**0.95*****	**0.96****	**0.95****	0.97
Drug offense				0.96	0.93	0.92	0.93
Property offense				1.08	1.08	1.07	**1.27****
Violent offense				1.09	1.05	1.05	1.00
Prob/parole violation				**1.21****	**1.22****	**1.22****	**1.30*****
SVORI: Time served[a]				0.98	0.96	**0.96***	**0.95***
Age at first arrest				0.97	0.98	0.98	0.98
Arrest sum (year before term)				**1.16*****	**1.15*****	**1.15*****	**1.09*****
Prison terms (*ref*. First term)							
1 previous term				1.16	1.15	1.11	**1.17***
2 previous terms				**1.41*****	**1.34****	**1.29****	**1.31****
3+ previous terms				**1.52*****	**1.39****	**1.32****	**1.40*****
Longest job tenure (*ref*. Less than 1 year)							
1 to 2 years					**0.79****	**0.79****	**0.84***
2 to 5 years					**0.71****	**0.71****	**0.76****
5 years or more					**0.69****	**0.67****	**0.74***
Work-release job					**0.56***	**0.58***	0.80
Prison industry job					1.01	1.01	0.93
Personal mastery scale						**0.87***	0.90
Global Severity Index (GSI)						1.00	1.00
Alcohol/drug use before prison						**1.26***	**1.22***
Racial/ethnic status (*ref*. African American)							
White							**0.84***
Hisp, multi, other, miss							0.79

SVORI site location (*ref*. South Carolina)							
Iowa							**0.72***
Indiana							1.23
Kansas							0.91
Maryland							**1.46*****
Missouri							**0.71***
Nevada							1.15
Ohio							0.96
Oklahoma							0.87
Pennsylvania							**0.39*****
Washington							**1.60*****
Log likelihood	-1855.2	-1849.7	-1773.6	-1671.1	-1628.8	-1612.6	-1480.0
BIC	3768.04	3798.19	3662.29	3539.69	3496.16	3488.32	3322.01

Note: N = 1,521; 3,734 obs. *HR* = Hazard ratio. Gompertz distribution with robust standard errors and clustering to account for repeated observations. "a" indicates continuous variables centered on state means. SVORI = Serious and Violent Offender Reentry Initiative. Ref. groups: Group 1, No previous prison term, Less than 1 year at any job, African American, South Carolina.
* $p < .05$, ** $p < .01$, *** $p < .001$.

Some characteristics reduced men's hazard of rearrest during the 3-year observation period. Compared to African American men, White men had a 16% reduction in the baseline hazard (*HR* = 0.84, $p = .021$). Increasingly long periods of employment at one job before prison also reduced men's risk of rearrest, in part because older men were more likely than young men to have held jobs for longer than a year (*HR* = 0.74-0.84, $p < .050$). Similarly, men who had completed longer prison terms were more likely to remain in the community: Each additional year served reduced men's relative risk of rearrest by 5% (*HR* = 0.95, $p = .014$).

Single-Event Failure Models

Results of the single-event failure models partially contradict results of the repeated-events duration model. Participants in education programs were arrested for non-violent arrests at faster rates than were employment program participants or nonparticipants (*HR* = 1.33-1.67, $p < .050$). The hazard ratios for education participation correspond to a 33% increase in the baseline hazard of any arrest, 52% increase for property arrest, and a 67% increase in the baseline hazard of drug arrest. In contrast, education participants showed longer times to first violent arrest, when compared to employment program participants or nonparticipants (*HR* = 0.76, *p* = .044). These results may provide evidence for reductions in violent offending among education participants, but the significant findings in the single-event models may be due to chance (e.g., measurement error due to separating out arrests by offense). Vocational education/job training programs were not associated with time to first arrest for any offense type (*HR* = 0.94-1.16, *p* > .100). Table 4.9 presents results of the single-failure duration models.

Table 4.9 Duration Models: Results for Time to First Arrest by Offense Type.

	Any arrest *HR (se)*	Drug arrest *HR (se)*	Property arrest *HR (se)*	Violent arrest *HR (se)*
Educ. programs	**1.33**** (0.12)	**1.67*** (0.41)	**1.52*** (0.30)	**0.76*** (.10)
Voc/job training	1.16 (0.15)	1.36 (0.28)	1.10 (0.15)	0.94 (0.11)
G1 Nonpart.	**3.08**** (1.28)	2.09 (1.18)	1.25 (1.27)	0.71 (0.58)
G1 Part.	1.57 (0.60)	0.79 (0.45)	0.71 (0.37)	1.59 (1.06)
G2 Nonpart.	1.52 (1.25)	0.88 (0.71)	0.69 (0.94)	0.75 (0.77)
G2 Part.	0.96 (0.73)	**0.24*** (0.15)	0.66 (0.78)	1.29 (1.22)
G3 Nonpart.	2.26 (1.19)	1.56 (1.09)	4.76 (5.51)	1.42 (1.31)
G3 Part.	1.61 (0.84)	0.43 (0.30)	1.30 (0.95)	2.38 (1.67)
Traj (*ref*. Grp 1)				
Group 2	1.39 (0.48)	**1.88***** (0.33)	1.17 (0.59)	0.94 (0.49)
Group 3	1.51 (0.44)	1.71 (0.69)	1.13 (0.74)	0.98 (0.37)
Age at release[a]	0.99 (0.02)	**0.97*** (0.02)	0.99 (0.02)	0.97 (0.02)
Education[a]	0.98 (0.02)	0.94 (0.03)	0.98 (0.03)	1.01 (0.03)
Drug offense	0.99 (0.16)	**1.86**** (0.38)	0.72 (0.14)	0.77 (0.17)
Property offense	1.39 (0.23)	0.90 (0.15)	**2.40**** (0.61)	1.06 (0.18)
Violent offense	1.04 (0.16)	1.03 (0.16)	0.75 (0.20)	1.23 (0.21)
Prob/parole viol.	**1.29**** (0.10)	1.16 (0.25)	**1.27*** (0.15)	**1.48**** (0.21)
Time served[a]	**0.93*** (0.03)	1.00 (0.04)	0.98 (0.03)	0.95 (0.03)
Age at 1st arrest	0.97 (0.02)	0.99 (0.04)	**0.91***** (0.02)	0.97 (0.02)
Arrests, last year	**1.12**** (0.04)	1.13 (0.08)	**1.10**** (0.04)	1.00 (0.09)
Prison (*ref*. None)				
1 prior term	1.19 (0.12)	1.42 (0.26)	1.08 (0.21)	0.85 (0.14)
2 prior terms	**1.37**** (0.13)	**2.06***** (0.41)	1.30 (0.19)	1.24 (0.25)
3+ prior terms	1.40 (0.28)	**1.59**** (0.27)	**1.61*** (0.34)	1.30 (0.29)
Job tenure				
1 to 2 years	0.79 (0.10)	**0.66*** (0.12)	**0.64**** (0.09)	0.87 (0.15)
2 to 5 years	**0.73**** (0.08)	**0.62**** (0.09)	**0.53***** (0.07)	0.93 (0.25)
5 years/more	**0.75*** (0.10)	0.68 (0.20)	0.80 (0.26)	1.11 (0.24)

Work-release	0.64 (0.17)	0.63 (0.16)	1.32 (0.52)	0.54 (0.22)
Prison job	0.85 (0.22)	0.62 (0.23)	0.75 (0.27)	0.98 (0.35)
Mastery scale	0.89 (0.06)	0.90 (0.21)	1.03 (0.22)	**0.70***** (0.05)
GSI	1.00 (0.00)	0.99 (0.00)	1.00 (0.00)	1.00 (0.00)
Alc/drug use	1.29 (0.17)	1.11 (0.20)	1.36 (0.25)	0.80 (011)
Race (*ref*. AfAm)				
White	**0.69***** (0.07)	**0.66*** (0.14)	1.15 (0.13)	0.81 (0.19)
Hisp/other/miss	**0.63***** (0.08)	0.87 (0.12)	0.69 (0.16)	**0.57**** (0.11)
SVORI site (*ref*. SC)				
Iowa	**0.86*** (0.05)	**1.34**** (0.15)	**0.58***** (0.04)	0.78 (0.10)
Indiana	1.04 (0.05)	**1.23**** (0.10)	0.88 (0.08)	**1.63***** (0.16)
Kansas	1.03 (0.08)	**0.75*** (0.10)	1.18 (0.12)	1.19 (0.14)
Maryland	**1.35***** (0.11)	**1.84***** (0.24)	**1.45*** (0.25)	1.11 (0.14)
Missouri	**0.72***** (0.03)	**1.27**** (0.09)	**0.37***** (0.04)	**0.32***** (0.04)
Nevada	1.24 (0.15)	1.05 (0.07)	**1.82***** (0.24)	1.18 (0.13)
Ohio	**0.77***** (0.04)	1.20 (0.13)	0.85 (0.12)	0.82 (0.12)
Oklahoma	1.07 (0.05)	**1.48***** (0.12)	**0.67***** (.0.06)	**0.78**** (0.07)
Pennsylvania	**0.60***** (0.05)	**1.24*** (0.13)	**0.30***** (0.06)	**0.45***** (0.06)
Washington	**1.82***** (0.12)	**1.94***** (0.25)	**1.60***** (0.20)	**1.52***** (0.12)
P	4.56	4.55	4.62	5.33
Log likelihood	-589.76	-697.18	-622.85	-593.47
BIC	1,252.79	1,467.64	1,318.98	1,260.20

Note: N = 1,521. *HR* = Hazard ratio. Standard errors in parentheses. Weibull distribution with robust standard errors and clustering at state site. "a" indicates continuous variables centered on state means. SVORI = Serious and Violent Offender Reentry Initiative. Ref. groups: Group 1, No previous prison term, Less than 1 year at any job, African American, South Carolina.
* $p < .05$, ** $p < .01$, *** $p < .001$.

4.6.5 Hypothesis 3: Increased Participation has Diminishing Benefits

The results provide support for Hypothesis 3. The duration models show that the effects of educational and job training programs are not consistent across offense types. However, rearrest rates for participants who received both education and employment programming were virtually identical to rearrest rates for participants receiving either education or employment services alone (presented in Figure 4.7 and Table 4.10). When compared to men who received only one type of service, men who engaged in educational and employment services exhibited more risk factors. These factors may have selected men to receive more services, but greater service receipt did not lead to significant differences in rearrest.

Table 4.10 Post-Release Labor Force Participation by Participant Status.

	Non Part. (*n* = 722)	Educ. Part. (*n* = 593)	Emp. Part. (*n* = 90)	Educ. & Emp. (*n* = 116)	*F*	*p*
Wave 2 (*n* = 899)						
Labor force exit	15.07	13.75	5.00	8.33	11.82***	<.001
No work since release	26.32	25.79	11.67	18.06	9.28***	<.001
Worked some months	43.06	42.69	48.33	40.28		
Worked all months	30.62	31.52	40.00	41.67		
Wave 3 (*n* = 939)						
Labor force exit	20.96	15.88	11.29	13.92	10.34**	.002
No work since release	26.20	21.45	14.52	21.52	5.86**	.003
Worked some months	45.10	47.35	51.61	43.04		
Worked all months	28.70	31.20	33.87	35.44		
Wave 4 (*n* = 1,008)						
Labor force exit	31.46	33.94	25.71	30.67	3.67	.057
No work since release	35.42	37.08	28.57	33.33	2.48	.086
Worked some months	34.38	32.38	34.29	33.33		
Worked all months	30.21	30.55	37.14	33.33		

Note: N = 899 at W2; N = 939 at W3; N = 1,008 at W4. Percentages generated using weights obtained from nearest neighbor matching. Design-based F statistic based on weighted data.
* $p < .05$, ** $p < .01$, *** $p < .001$.

4.7 Structural Equation Modeling

4.7.1 Outcome variables

Post-Release Labor Force Participation

Approximately 31% of men worked consistently during each follow-up interview reference period (32.32% for months 1-3 [W2], 30.51% for months 4-9 [W3], 31.17% for months 10-15 [W4]). Average number of hours worked each week increased over the three follow-up periods, but the proportion of men who held permanent jobs with formal pay declined between the third and fourth interviews. The jobs men held at months 10-15 (W4) were also slightly less likely to provide health benefits and paid time off than the jobs men held during months 4-9 (W3), but these differences may reflect simple variations in the composition of employed men during each reference period.

Post-Release Crime and Criminal Justice Involvement

Self-reported criminal activity increased from the second to third wave interviews (from months 1-3 to months 4-9). Approximately one in five respondents admitted to any crimes during the first 3 months of release (21.11%), but this percentage increased to one in three by Waves 3 and 4 (36.89% at W3, 35.44% at W4). Rates of rearrest and return to prison increased throughout the observation period. After 21 months following release from prison, 63.45% of the men in the sample had been arrested at least once, and 39.84% had returned to prison on a technical violation or new charge.

Table 4.11 Model Fit Statistics for the Tests of Configural Invariance over Four Waves.

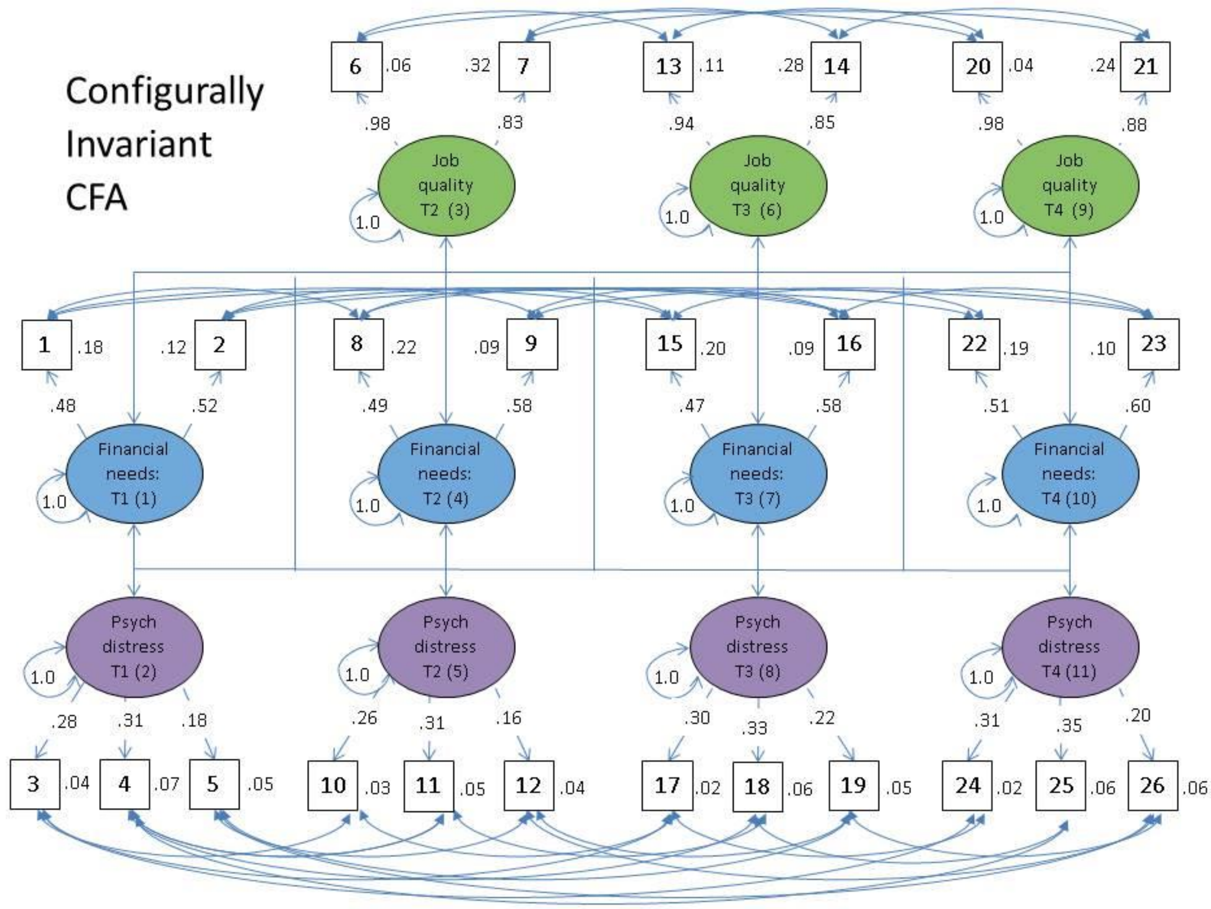
Model tested	χ^2	*df*	$\Delta\chi^2$	*p*	RMSEA	90% CI	CFI	ΔCFI	TLI	ΔTLI
Configural	301.00	208			.019	.014;.024	.993		.987	
Weak	322.67	219	21.24	.031	.019	.015;.024	.992	.001	.987	.000
Strong	364.45	230	41.78	<.001	.022	.017;.026	.990	.002	.984	.003

Note: *N* = 1,245. CI = Confidence Interval for RMSEA. CFI = Comparative Fit Index. ΔCFI = Change in the CFI. *df* = Chi square degrees of freedom. RMSEA = Root Mean Square Error of Approximation. TLI = Tucker-Lewis Index (Non-Normed Fit Index). ΔTLI = Change in the TLI. Configural = configurally invariant model; weak = weak invariant model; strong = strong invariant model.

4.7.2 Confirmatory Factor Model

Tests of Factorial Invariance

The measurement model fit 11 latent factors, encapsulating financial need and psychological distress at each analysis period, and job quality at the second, third, and fourth waves. Table 4.11 presents model fit statistics for the tests of factorial invariance. The results suggest that the 11-factor measurement model met the requirements of strong factorial invariance.



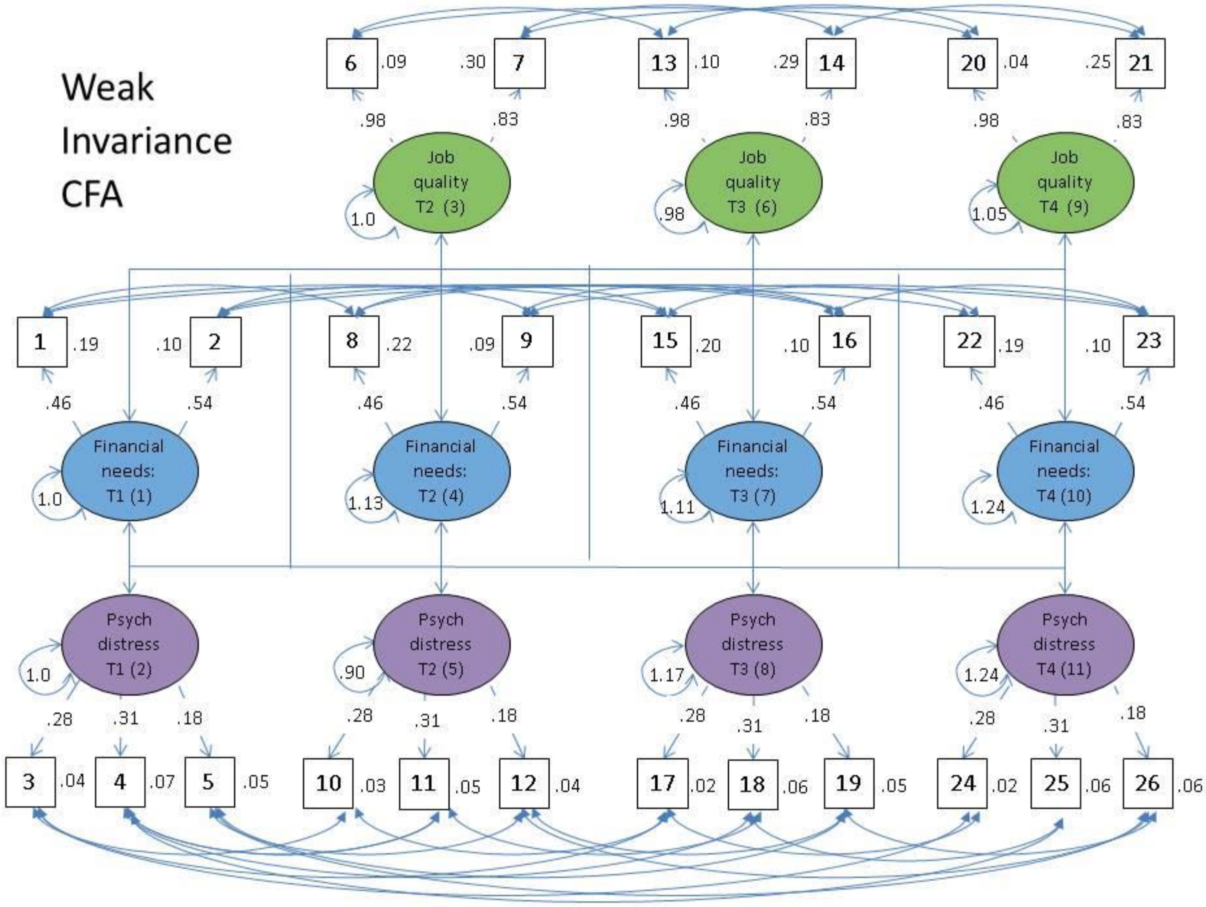
Construct	Items	Definition
Labor force attachment		
Primary sector employment	6, 13, 20	Standardized index of recent job quality: permanency, formal pay, benefits
Work week	7, 14, 21	Standardized scale: Average hours worked each week at most recent job
Financial needs		
Parcel 1	1, 8, 15, 22	Average need: place to live, clothing banks/food pantries, financial assistance
Parcel 2	2, 9, 16, 23	Average need: transportation, public financial assistance, public healthcare insurance
Psychological distress		
Anxiety subscale	3, 10, 17, 24	Log-transformed average: Anxiety items
Depression subscale	4, 11, 18, 25	Log-transformed average: Depression items
Hostility subscale	5, 12, 19, 26	Log-transformed average: Hostility items

Figure 4.8 Parameter Estimates for Four Time Points: The Configural Invariance Model.

The configurally invariant model showed good model fit (RMSEA = .019 [.014;.024], CFI = .993, TLI = .987). The items exhibited similar pattern loadings over time; for the financial needs factor, the second item had the largest loading, the first item had the smallest loading, and the third item was in the middle. Among psychological distress indicators, the depression parcel loaded strongest on the latent factor, followed by the anxiety and hostility parcels. For the job quality factors, the standardized primary sector employment item had larger loadings than did the standardized workweek item. Figure 4.8 presents results of the configural invariance model.

The indicators and factors also passed the test for weak factorial invariance. When factor loadings were constrained to equality at each wave, the fit statistics indicated no decline in the fit of the overall model (RMSEA = .019 [.015;.024], CFI = .992, TLI = .987). Figure 4.9 presents results of the weak factorial invariance model.

To test strong factorial invariance, the factor loadings and intercepts were constrained to equal the values for the first observation period. The intercepts for financial need items at Wave 1 were slightly higher than intercepts at subsequent waves, so constraining the intercepts to equal the Wave 1 items had the most notable effect on the change. Nonetheless, the model fit statistics indicate that the strong invariance model showed good fit (RMSEA = .022 [.017;.026], CFI = .990, TLI = .984), the change in CFI of .002 did not exceed the .002 maximum change that Meade, Johnson, and Braddy (2008) recommend. Table 4.12 presents parameter estimates for different levels of factorial invariance. Figure 4.10 presents the retained CFA model, and it is used to build the longitudinal structural equation model.



Construct	Items	Definition
Labor force attachment		
Primary sector employment	6, 13, 20	Standardized index of recent job quality: permanency, formal pay, benefits
Work week	7, 14, 21	Standardized scale: Average hours worked each week at most recent job
Financial needs		
Parcel 1	1, 8, 15, 22	Average need: place to live, clothing banks/food pantries, financial assistance
Parcel 2	2, 9, 16, 23	Average need: transportation, public financial assistance, public healthcare insurance
Psychological distress		
Anxiety subscale	3, 10, 17, 24	Log-transformed average: Anxiety items
Depression subscale	4, 11, 18, 25	Log-transformed average: Depression items
Hostility subscale	5, 12, 19, 26	Log-transformed average: Hostility items

Figure 4.9 Parameter Estimates for Four Time Points: The Weak Invariance Model.

Table 4.12 Comparison of Parameter Estimates across the Levels of Invariance.

Parameter	Factor	Item	Symbol	Configural	Weak	Strong
Factor loadings						
Financial	1	1	$\lambda_{1,1}$	0.484	0.459	0.472
Needs		2	$\lambda_{2,1}$	0.517	0.542	0.530
	4	8	$\lambda_{8,4}$	0.486	0.459[a]	0.472[a]
		9	$\lambda_{9,4}$	0.576	0.542[a]	0.530[a]
	7	15	$\lambda_{15,7}$	0.469	0.459[a]	0.472[a]
		16	$\lambda_{16,7}$	0.584	0.542[a]	0.530[a]
	10	22	$\lambda_{22,10}$	0.513	0.459[a]	0.472[a]
		23	$\lambda_{23,10}$	0.602	0.542[a]	0.530[a]
Psychological	2	3	$\lambda_{3,2}$	0.276	0.277	0.277
Distress		4	$\lambda_{4,2}$	0.314	0.312	0.313
		5	$\lambda_{5,2}$	0.183	0.183	0.181
	5	10	$\lambda_{10,5}$	0.261	0.277[a]	0.277[a]
		11	$\lambda_{11,5}$	0.310	0.312[a]	0.313[a]
		12	$\lambda_{12,5}$	0.157	0.183[a]	0.181[a]
	8	17	$\lambda_{17,8}$	0.299	0.277[a]	0.277[a]
		18	$\lambda_{18,8}$	0.326	0.312[a]	0.313[a]
		19	$\lambda_{19,8}$	0.216	0.183[a]	0.181[a]
	11	24	$\lambda_{24,11}$	0.308	0.277[a]	0.277[a]
		25	$\lambda_{25,11}$	0.350	0.312[a]	0.313[a]
		26	$\lambda_{26,11}$	0.202	0.183[a]	0.181[a]
Job quality	3	6	$\lambda_{6,3}$	0.975	0.960	0.960
		7	$\lambda_{7,3}$	0.831	0.848	0.849
	6	13	$\lambda_{13,6}$	0.943	0.960[a]	0.960[a]
		14	$\lambda_{14,6}$	0.848	0.848[a]	0.849[a]
	9	20	$\lambda_{20,9}$	0.981	0.960[a]	0.960[a]
		21	$\lambda_{21,9}$	0.876	0.848[a]	0.849[a]
Variances						
Financial	1	1	$\theta_{1,1}$	0.176	0.194	0.185
needs		2	$\theta_{2,2}$	0.124	0.101	0.115
	4	8	$\theta_{8,8}$	0.220	0.220	0.213
		9	$\theta_{9,9}$	0.089	0.088	0.102
	7	15	$\theta_{15,15}$	0.204	0.198	0.191
		16	$\theta_{16,16}$	0.089	0.099	0.110
	10	22	$\theta_{22,22}$	0.186	0.188	0.179
		23	$\theta_{23,23}$	0.097	0.095	0.107
Psychological	2	3	$\theta_{3,3}$	0.040	0.040	0.040
distress		4	$\theta_{4,4}$	0.065	0.065	0.065
		5	$\theta_{5,5}$	0.051	0.051	0.051
	5	10	$\theta_{10,10}$	0.028	0.027	0.027
		11	$\theta_{11,11}$	0.045	0.049	0.048
		12	$\theta_{12,12}$	0.044	0.043	0.043

Table 4.12 Comparison of Parameter Estimates across the Levels of Invariance.

Parameter	Factor	Item	Symbol	Configural	Weak	Strong
Variances						
Psychological distress	8	17	$\theta_{17,17}$	0.024	0.024	0.024
		18	$\theta_{18,18}$	0.058	0.057	0.056
		19	$\theta_{19,19}$	0.050	0.051	0.052
	11	24	$\theta_{24,24}$	0.023	0.023	0.023
		25	$\theta_{25,25}$	0.057	0.057	0.057
		26	$\theta_{26,26}$	0.055	0.055	0.055
Job quality	3	6	$\theta_{6,6}$	0.060	0.086	0.086
		7	$\theta_{7,7}$	0.316	0.297	0.297
	6	13	$\theta_{13,13}$	0.113	0.102	0.103
		14	$\theta_{14,14}$	0.281	0.289	0.289
	9	20	$\theta_{20,20}$	0.044	0.037	0.037
		21	$\theta_{21,21}$	0.239	0.245	0.245
Financial needs	1	Latent factor	$\psi_{1,1}$	1.000*	1.000*	1.000*
	4		$\psi_{4,4}$	1.000*	1.129	1.128
	7		$\psi_{7,7}$	1.000*	1.110	1.110
	10		$\psi_{10,10}$	1.000*	1.239	1.244
Psychological Distress	2	Latent factor	$\psi_{2,2}$	1.000*	1.000*	1.000*
	5		$\psi_{5,5}$	1.000*	0.896	0.896
	8		$\psi_{8,8}$	1.000*	1.174	1.172
	11		$\psi_{11,11}$	1.000*	1.239	1.239
Job quality	3	Latent factor	$\psi_{3,3}$	1.000*	1.000*	1.000*
	6		$\psi_{6,6}$	1.000*	0.979	0.979
	9		$\psi_{9,9}$	1.000*	1.054	1.054
Intercepts						
Financial needs	1	1	τ_1	1.052	1.052	1.029
		2	τ_2	1.089	1.089	1.104
	4	8	τ_8	0.848	0.847	1.029[a]
		9	τ_9	0.950	0.950	1.104[a]
	7	15	τ_{15}	0.832	0.832	1.029[a]
		16	τ_{16}	0.895	0.894	1.104[a]
	10	22	τ_{22}	0.811	0.811	1.029[a]
		23	τ_{23}	0.865	0.865	1.104[a]
Psychological distress	2	3	τ_3	0.347	0.347	0.335
		4	τ_4	0.428	0.428	0.430
		5	τ_5	0.195	0.195	0.209
	5	10	τ_{10}	0.240	0.239	0.335[a]
		11	τ_{11}	0.309	0.309	0.430[a]
		12	τ_{12}	0.147	0.147	0.209[a]

Table 4.12 Comparison of Parameter Estimates across the Levels of Invariance.

Parameter	Factor	Item	Symbol	Configural	Weak	Strong
Intercepts						
Psychological	8	17	τ_{17}	0.270	0.270	0.335[a]
distress		18	τ_{18}	0.373	0.373	0.430[a]
		19	τ_{19}	0.187	0.186	0.209[a]
	11	24	τ_{24}	0.288	0.288	0.335[a]
		25	τ_{25}	0.386	0.386	0.430[a]
		26	τ_{26}	0.190	0.190	0.209[a]
Job quality	3	6	τ_{6}	-0.044	-0.044	-0.043
		7	τ_{7}	-0.033	-0.035	-0.036
	6	13	τ_{13}	-0.045	-0.045	-0.043[a]
		14	τ_{14}	-0.035	-0.034	-0.036[a]
	9	20	τ_{20}	-0.006	-0.006	-0.043[a]
		21	τ_{21}	-0.005	-0.005	-0.036[a]
Financial	1	Latent	α_{1}	0.000*	0.000*	0.000*
Needs	4	factor	α_{4}	0.000*	0.000*	-0.320
	7		α_{7}	0.000*	0.000*	-0.401
	10		α_{10}	0.000*	0.000*	-0.455
Psychological	2	Latent	α_{2}	0.000*	0.000*	0.000*
Distress	5	factor	α_{5}	0.000*	0.000*	-0.360
	8		α_{8}	0.000*	0.000*	-0.206
	11		α_{11}	0.000*	0.000*	-0.158
Job quality	3	Latent	α_{3}	0.000*	0.000*	0.000*
	6	factor	α_{6}	0.000*	0.000*	-0.001
	9		α_{9}	0.000*	0.000*	0.039
X^2				301.004	322.669	364.445
df				208	219	230
RMSEA				.019	.019	.022
RMSEA 90% CI				.014;.024	.015;.024	.017;.026
CFI				.993	.992	.990
TLI/NNFI				.987	.987	.984

Note. *N* = 1,245. Configural = configurally invariant model; weak = weak invariance model; strong = strong invariance model. *Indicates that the value is fixed to set the scale of the constructs' parameter estimates. "a" indicates that the estimate is constrained to be equal to the preceding time point.

Measurement Model

The financial need factor loadings ranged from .47 to .53, psychological distress parcels ranged from .18 to .31, and the loadings for job quality ranged from .85 to .96. Intercepts for each construct were constrained to equal the intercepts for the first observation period (Wave 1 for financial needs and psychological distress, Wave 2 for job quality). Intercepts for the financial need parcels ranged from 1.03 to 1.10. The job quality intercepts were constrained to their Wave

2 values (-0.04 for standardized number of hours work each week, -0.04 for standardized primary sector employment index), with negligible impact on model parameter estimates.

The mean value for latent financial needs declined from 0.00 at release to -0.46 by the fourth interview. The results suggest that financial needs declined slightly over time, with financial needs at their highest as men were preparing to leave prison. Mean psychological distress declined from 0.00 at the first wave to its lowest level at Wave 2 (-0.36), after which it increased slightly by the third and fourth interviews (Wave 3 = -0.21, Wave 4 = -0.16). The mean values for latent job quality at Waves 3 and 4 were not significantly differently from 0.00 (Wave 3 = -0.00, Wave 4 = 0.04).

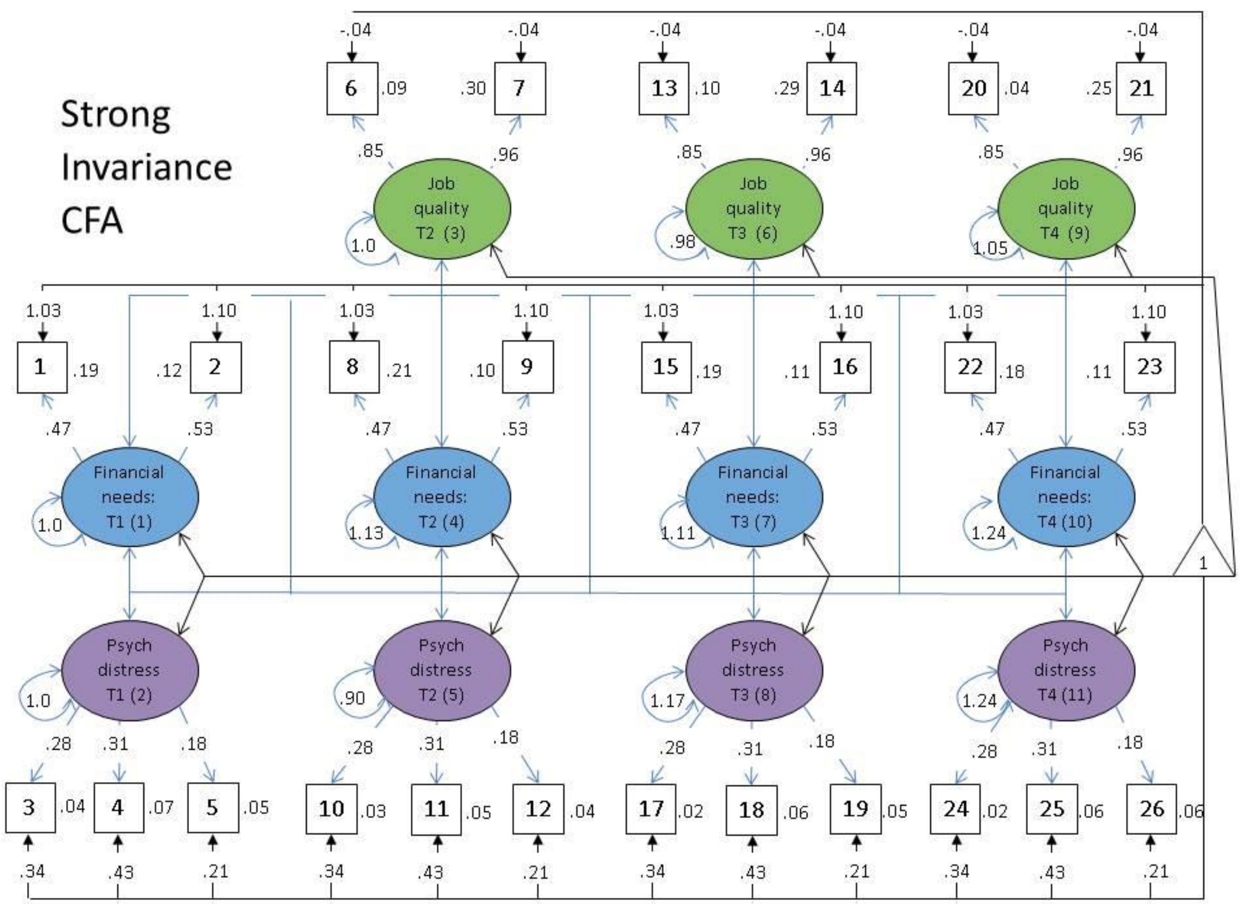


Figure 4.10 Parameter Estimates for Four Time Points: The Strong Invariance Model.

4.7.3 Structural Equation Path Model

Findings from the longitudinal structural equation model provide partial support for the hypotheses presented in Chapter 3. Tables 4.13 and 4.14 present results of the longitudinal structural equation model, controlling for the effect of covariates described in the Measures section. Table 4.13 presents unstandardized coefficients for all paths between the latent factors and observed variables. Table 4.14 presents odds ratios for work, crime, and recidivism outcomes at each follow-up interview. Figure 4.11 presents the final longitudinal structural equation model.

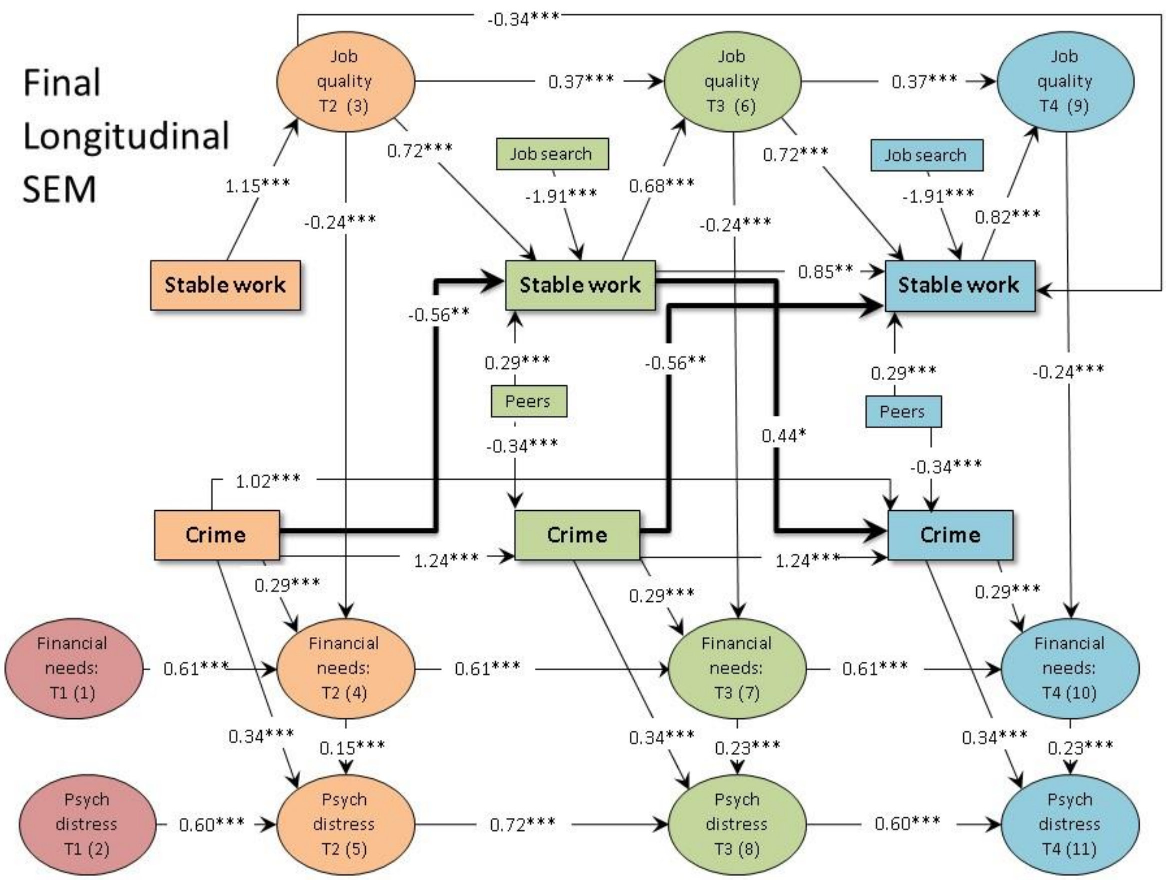


Figure 4.11 Final Longitudinal Structural Equation Path Model.

4.7.4 Hypothesis 4: Criminal Activity Reduces Human and Social Capital

Results provide limited evidence to assess whether ongoing criminal involvement reduces men's stock of human and social capital. The final path includes paths from prosocial peer influences to crime and criminal justice involvement, not from crime to later investments in human and social capital. However, the path model shows an association between positive peer influences (friends who work and do not get in trouble) and reduced odds of having committed crimes recently. Compared to men who reported that most of their friends were positive influences, men who said that all of them were had 29% lower odds of having committed crime during the interview reference period (Waves 3 and 4: *OR* = 0.71, b = -0.34, $p < .001$). Similarly, prosocial peer influences at the Wave 3 interview (months 3-9) reduced men's odds of returning to prison during the first 21 months of release (*OR* = 0.77, b = -0.27, p = .005).

Men who were arrested within the first 90 days were significantly less likely than other men to remain employed during the subsequent 6-month period (*OR* = 0.47, b = -0.75, $p < .001$). Arrests that occurred within the first 9 months had a similar effect of Wave 4 employment, reducing the odds of remaining stably employed between months 10 and 15 by 53% (*OR* = 0.47, b = -0.75, $p < .001$). Reincarceration further reduced men's odds of maintaining stable employment by the time of the Wave 4 interview (*OR* = 0.44, b = -0.83, p = .014).

4.7.5 Hypothesis 5: Human and Social Capital Increases Employment

Path model results support this hypothesis. Men who had worked at the same place for longer than 1 year, at any point before entering prison, continued to have more success in maintaining employment upon release, compared to men who had never worked anywhere for longer than a year (*OR* = 1.81-3.32). Men who experienced greater job difficulties during each reference period had reduced odds of maintaining stable employment. Men who reported experiencing all six barriers to employment had 85-90% lower odds of working each month (*OR* = 0.15, *b* = -1.91, *p* < .001). During each observation period, prosocial peer influences increased men's labor force attachment. Compared to men who reported that most of their friends were positive influences, men who said all of them were had 30% higher odds of maintaining stable employment (*OR* = 1.34, *b* = 0.29, *p* < .001).

4.7.6 Hypothesis 6: Labor Force Participation Increases Job Quality

Several pathways within the longitudinal structural equation model provide support for this hypothesis. Consistent employment (e.g., working each month) was associated with improved job quality within the same interview reference period. The largest coefficient for stable employment was at the first follow-up interview (Wave 2, 3 months after release). Mean job quality was 1 standard deviation increase higher among men who had worked each month since release, in comparison to men who worked intermittently or not at all.

The association between stable employment and job quality was smaller at subsequent interviews, although the effect of stable employment on job quality increased slightly from months 4-9 (Wave 3) to months 10-15 (Wave 4). Men who worked consistently during the Wave 3 reference period reported higher quality jobs than did men who had not maintained stable employment during the same timeframe (*b* = 0.68, *p* < .001). During the subsequent 6 months (months 10-15), stable employment was associated with slightly larger improvements in job quality (*b* = 0.82, *p* < .001).

Table 4.13 Longitudinal Structural Equation Model.

	Wave 2 *b (se)*	Wave 3 *b (se)*	Wave 4 *b (se)*
Stable employment			
Recent job difficulties		-1.91*** (0.27)	-1.91***[a] (0.27)
Recent prosocial peers		0.29*** (0.08)	0.29***[a] (0.08)
Stable employment, Wave 2		0.39 (0.22)	0.33 (0.28)
Stable employment, Wave 3			0.85** (0.25)
Job quality, Wave 2		0.72*** (0.11)	-0.34 (0.16)
Job quality, Wave 3			0.72***[a] (0.11)
Criminal activity, Wave 2		-0.56** (0.18)	0.08 (0.32)
Criminal activity, Wave 3			-0.56**[a] (0.18)
Job quality			
Recent stable employment	1.15*** (0.07)	0.68*** (0.07)	0.82*** (0.07)
Prior job quality		0.37*** (0.03)	0.37***[a] (0.03)
Financial need			
Prior financial needs	0.61*** (0.03)	0.61***[a] (0.03)	0.61***[a] (0.03)
Recent criminal activity	0.29*** (0.04)	0.29***[a] (0.04)	0.29***[a] (0.04)
Current job quality	-0.24*** (0.02)	-0.24***[a] (0.02)	-0.24***[a] (0.02)
Psychological distress			
Current financial needs	0.15*** (0.03)	0.23*** (0.03)	0.23***[a] (0.03)
Prior psych distress	0.60*** (0.03)	0.72*** (0.05)	0.60***[a] (0.03)
Recent criminal activity	0.34*** (0.04)	0.34***[a] (0.04)	0.34***[a] (0.04)
New crime			
Recent prosocial peers		-0.34*** (0.06)	-0.34***[a] (0.06)
Stable employment, Wave 2		-0.11 (0.19)	-0.13 (0.21)
Stable employment, Wave 3			0.44* (0.21)
Criminal activity, Wave 2		1.24*** (0.14)	1.02*** (0.24)
Criminal activity, Wave 3			1.24***[a] (0.06)
Recidivism		**Arrest (12 Mth)**	**Return (21 Mth)**
Prosocial peers		-0.12 (0.09)	-0.27** (0.09)
Stable employment, Wave 2		0.12 (0.23)	-0.02 (0.25)
Stable employment, Wave 3		-0.63** (0.22)	-0.70** (0.23)
Job quality, Wave 2		0.16 (0.13)	0.50** (0.16)
Job quality, Wave 3		-0.55*** (0.11)	-0.78*** (0.14)
Criminal activity, Wave 2		-0.12 (0.23)	-0.25 (0.23)
Criminal activity, Wave 3		1.02*** (0.18)	-0.92*** (0.18)

Note: N = 1,243. AIC = 40,461.142. Covariates regressed on endogenous constructs and observed variables. Covariates include age, education, racial/ethnic status, criminal record, risk factors, pre-SVORI alcohol or drug use, and state location. SVORI = Serious and Violent Offender Reentry Initiative. “a” indicates that the estimate is constrained to be equal to the preceding time point.
* $p < .05$, ** $p < .01$, *** $p < .001$.

Labor force participation also had an indirect effect on later job quality, through its effect on later employment and through lagged effects of job quality on both later employment and later job quality. First, consistent employment during the Wave 3 reference period (months 4-9) more than doubled the odds of maintaining employment throughout the following 6 months (OR = 2.34, $b = 0.85$, $p = .001$). This association persisted after accounting for self-reported criminal activity at Waves 2 and 3, employment status at Wave 2, and criminal justice involvement (arrest within the first 3 months of release, return to prison within the first 3 months). In contrast, when controlling for criminal activity and criminal justice involvement during the first few months of release, stable employment during the Wave 2 reference period had no effect on the likelihood of remaining employed during the subsequent 6 months (OR = 1.47, $b = 0.39$, $p = .073$).

Second, men who held higher-quality jobs at the current interview were more likely to work consistently each month of the next interview period. A 1-unit increase in latent job quality doubled the odds of working consistently during the subsequent 6 months (OR = 2.06, $b = 0.72$, $p < .001$). Finally, the lagged effect of job quality on later job quality was significant at each wave ($b = 0.37$, $p < .001$). In sum, the results show that men who obtained work immediately upon release from prison were more likely to remain employed and to obtain higher quality employment over time. Attributes about the individuals, and about the jobs they obtained, may help explain the significant associations between consistent labor force participation and higher quality, primary sector employment.

Table 4.14 Odds Ratios for Work, Crime, and Recidivism.

	Work		Crime		Arrest	Return
	W3	**W4**	**W3**	**W4**	**12 Mth**	**21 Mth**
Recent job difficulties	0.15***	0.15***	---	---	---	---
Recent positive peers	1.34***	1.34***	0.71***	0.71***	0.89	0.77**
Stable employment, Wave 2	1.47	1.39	0.90	0.88	1.13	0.98
Stable employment, Wave 3	---	2.34**	---	1.56*	0.54**	0.50**
Job quality, Wave 2	2.06***	0.71*	---	---	1.17**	1.65**
Job quality, Wave 3	---	2.06***	---	---	0.58***	0.46***
Criminal activity, Wave 2	0.57**	1.09	3.45***	2.78***	0.89	0.78
Criminal activity, Wave 3	---	0.57**	---	3.45***	2.77***	2.52***
Age at release	0.80	1.48*	0.82	1.00	0.72*	0.66*
Education	0.57	2.17	0.76	0.96	0.56	0.75
White (*ref.* African American)	0.74	1.31	1.73**	1.50*	0.71*	0.86
Hisp, multi, other, miss	0.93	1.10	1.37	1.27	0.88	1.43
Trajectory group 2 (*ref.* Group 1)	1.00	0.93	0.84	0.93	0.70	1.09
Trajectory group 3	0.65	0.48*	0.78	0.91	1.26	1.86**
Sum arrests, year before prison	0.81*	1.06	1.23*	1.06	1.16	1.04
SVORI term: Drug offense	0.78	0.84	1.42	0.95	0.80	0.80
SVORI term: Property offense	1.07	0.63	1.37	1.40	1.03	0.99
SVORI term: Violent offense	0.80	0.97	1.12	1.04	0.87	0.98
SVORI term: Parole/prob. viol.	0.76	0.97	1.46*	1.38	1.02	1.02
SVORI term: Time served	1.40	1.22	0.87	0.65	0.69	1.88
1 prior prison term (*ref.* None)	1.14	0.73	1.17	0.81	1.12	1.10
2 prior prison terms	0.66	0.55*	1.69*	0.85	1.56*	1.59*
3+ prior prison terms	1.13	0.90	1.58	0.72	1.43	1.37
Job tenure: 1-2 years (*ref.* < 1)	1.85*	1.31	0.83	0.81	1.13	1.08
2 to 5 years	1.81*	1.51	1.02	0.85	0.82	0.87
5 years/more	3.32***	0.94	0.92	0.72	0.79	1.12
Rearrest, previous period	0.47***	0.47***	1.21	0.84	---	---
Return to prison, previous period	0.68	0.44*	0.25**	0.63*	---	---
Pre-SVORI alcohol/drug use	0.86	0.92	1.50*	2.47***	1.43	1.30
Completed interviews	3.91***	1.12	1.00	0.68**	0.63***	0.94
Iowa	0.53	1.17	1.31	1.07	0.76	5.04***
Indiana	1.52	1.20	0.61	1.07	1.18	0.71
Kansas	0.29*	0.70	2.26	1.17	0.55	1.00
Maryland	0.70	1.21	1.45	1.11	1.31	0.83
Missouri	0.30*	0.39	1.63	1.57	0.52	1.69
Nevada	0.96	0.58	1.12	1.53	2.35**	2.79**
Ohio	1.22	1.53	1.65	1.44	0.88	0.85
Oklahoma	1.98	0.68	1.54	2.18*	0.43*	0.41*
Pennsylvania	0.38*	0.67	1.51	0.71	0.26***	3.06***
Washington	0.64	0.20**	2.82**	2.43*	1.19	0.08***

Note: N = 1,243. AIC = 40,461.142. Covariates regressed on endogenous constructs and observed variables. SVORI = Serious and Violent Offender Reentry Initiative. Ref. groups: African American, Group 1, No previous prison term, Less than 1 year at any job, South Carolina. "a" indicates that the estimate is constrained to be equal to the preceding time point.
* p < .05, ** p < .01, *** p < .001.

4.7.7 Hypothesis 7: Quality Jobs Reduce Men's Financial Needs

The structural equation path models provide support for this hypothesis. At each follow-up analysis period, job quality was significantly associated with reduced financial needs (Waves 2-4: $b = -0.24$, $p < .001$). Nonetheless, improved job quality did not fully address existing financial needs, as previous financial need remained significantly associated with current need ($b = 0.61$, $p < .001$).

4.7.8 Hypothesis 8: Financial Needs Increase the Probability of Reoffending

The results provide mixed evidence in support of this hypothesis. The original theoretical model specified that financial needs predicted concurrent criminal involvement. The model was revised to reflect the temporal ordering of financial need and crime items, so the paths go from prior financial need to recent criminal involvement and from recent criminal involvement to current financial needs.

The paths from recent criminal activity to current financial needs were significant at each follow-up interview period (constrained to equality, $b = 0.29$, $p < .001$). The coefficient suggests that current financial need was 1/2 standard deviation higher among those who had engaged in criminal activity during the preceding 3-6 month period. The LSEM results presented exclude the paths from prior financial need to recent self-reported criminal involvement, as these paths were not significant and diminished model fit (higher AIC).

4.7.9 Hypothesis 9: Financial Needs Increase Psychological Distress

The 15 indicators for psychological distress (5 indicators of anxiety, 5 of distress, and 5 of hostility) fit weakly on a latent factor. The hostility items exhibited the lowest factor loadings ($\lambda = 0.18$), but the anxiety and depression parcels were also extremely low ($\lambda = 0.27$ and $\lambda = 0.31$, respectively). The self-efficacy and locus of control items did not fit a CFA model at all. These personal mastery items were excluded from the final model because they correlated more strongly with other items (e.g., personal peer networks, psychological distress, and financial needs) than with each other.

Despite these revisions, results support this hypothesis. Men who reported more unmet financial needs also reported higher mean levels of psychological distress at each time point (Wave 2, b = 0.15, $p < .001$; constrained to equality at Waves 3 and 4, b = 0.23, $p < .001$). However, previous psychological distress accounted for much of the variation in current psychological distress at each follow-up period (Waves 2 & 4: b = 0.60, $p < .001$; Wave 3: b = 0.72, $p < .001$).

4.7.10 Hypothesis 10: Psychological Distress Contributes to Reoffending

The pathways from latent psychological distress to new crime within the next 3-6 months were not significant at each wave and were excluded from the final model. However, men who admitted to crime within the preceding 6 months reported heightened feelings of psychological distress. At each follow-up interview, self-reported criminal activity was associated with a 0.34 increase in latent psychological distress (b = 0.34, $p < .001$). In contrast, involvement in the criminal justice system during the months preceding each interview's 6-month reference period (for Wave 3, months 3-9: arrest or return to prison before 3 months; for Wave 4, months 10-15: arrest or return to prison before 9 months) had no effect on men's feelings of psychological distress. Psychological distress was not associated with likelihood of rearrest within the first 12 months or return to prison within the first 21 months (paths omitted from the final model).

4.7.11 Work-Crime Association

The results provide limited support for unidirectional theories of work and crime. The effect of work on crime varied across waves. Stable employment at Wave 2 was not associated with criminal activity at Wave 3 (OR = 0.90, b = -0.11, p = .578) or at Wave 4 (OR = 0.88, b = -0.13, *p* = .534). However, men who worked each month before the Wave 3 interview (months 4-9) had a 56% increase in the odds of committing crimes during the fourth interview reference period (months 10-15: *OR* = 1.56, *b* = 0.44, *p* = .033).

Criminal activity had a more consistent, persistent effect on later work and crime. Engaging in crime more than tripled the odds of reoffending within the following interview period (Waves 3 and 4, constrained to equality: *OR* = 3.45, *b* = 1.24, *p* <.001). After accounting for previous labor force and criminal activity, the lagged effect of Wave 2 crime on Wave 4 crime was nearly as large (*OR* = 2.78, *b* = 1.02, *p* <.001). In contrast, engaging in crime was associated with a 43% decline in the odds of remaining employed during the next wave (*OR* = 0.57, *b* = -0.56, *p* = .002). The effect of Wave 2 crime on later employment did not persist to Wave 4, when controlling for criminal activity during Wave 3 (*OR* = 1.09, *b* = 0.08, *p* = .793).

Significant associations between stable employment and criminal justice involvement did provide support for theories that link labor force participation to reduced recidivism. After controlling for labor force and criminal activity during the first 9 months of release (Waves 2 and 3), consistent employment at Wave 3 was associated with a 46% reduction in the odds of arrest during the first 12 months of release (*OR* = 0.54, *b* = -0.63, *p* = .005). Stable employment during that period had a similar effect on the likelihood of returning to prison within the first 21 months (*OR* = 0.50, *b* = -0.70, *p* = .002).

4.7.12 Trimmed Pathways from the Final Longitudinal SEM

The final model excludes paths from employment status and the latent job quality factor to psychological distress. These paths were not significant at any stage of model-fitting, and overall fit of the model improved when these paths were eliminated (based on log-likelihood and AIC values). Psychological distress was also not associated with subsequent labor force participation or job quality. The other main paths that were eliminated from the model were from prior job quality to current criminal activity. These paths were not significant at any wave.

4.7.13 Significant Covariates

Criminal Activity

Men who reported using alcohol or illicit drugs during the final month before their SVORI prison term were significantly more likely to remain engaged in crime during the three follow-up periods (Wave 3: *OR* = 1.50, *b* = 0.41, *p* = .047; Wave 4: *OR* = 2.47, *b* = 0.90, *p* <.001). Whites were significantly more likely than African American men were to report having committed crimes since release from prison: 73% higher odds at Wave 3 (*OR* = 1.73, *b* = 0.55, *p* = .004) and 50% higher odds at Wave 4 (*OR* = 1.50, *b* = 0.40, *p* = .034). However, White men had a decline of 29% in the odds of rearrest within the first 12 months, when compared to African American men (*OR* = 0.71, *b* = -0.34, *p* = .047).

4.8 Conclusion

Overall, the results show that the trajectory and propensity score models reduced pre-existing differences that had biased the initial SVORI evaluation findings. After matching participants and nonparticipants, the duration models show that education and employment programs have no long-term effects on employment and rearrest. Employment program participants were slightly more likely to seek and maintain employment during the first 9 months of release than other men were, and they were less likely to be arrested during the same timeframe. Conversely, education participants exhibited slightly increased risk of rearrest for certain crimes, but they showed slightly reduced risk of rearrest for violent crimes. Educational programming did not appear to improve men's post-release work outcomes, when compared to nonparticipants.

The results of the longitudinal structural equation model help explain the null effects of education and employment programming on recidivism. Criminal activity reduced the odds that men would maintain employment during subsequent waves, and the effects of early criminal involvement persisted over time. In contrast, employment did not appear to reduce the odds of engaging in crime at any Wave; consistent employment during the third wave even appeared to increase men's risk of engaging in crime during the fourth wave. However, the overall results suggest that the effects of criminal activity are more stable and persistent than are the effects of work on criminal activity. These findings are discussed in greater detail in the following chapter.

Chapter 5: Discussion

5.1 Summary of Findings

After controlling for pre-imprisonment characteristics and selection into employment-focused programming, the results show that vocational education and job training services do not have long-term effects on labor force participation or likelihood of rearrest. Men who received these services exhibited short-term increases in employment, as well as short-term delays in rearrest, but no significant differences persisted after the first 9 months of release. Furthermore, the five duration models consistently showed that employment programs had no effect on times to rearrest.

Results of the cross-lagged LSEM provide limited evidence to support theories of crime (or program logic models) that link increased labor force activity to reductions in later offending. When recidivism was measured as new arrest within 12 months, and as reincarceration within 21 months, increased labor force attachment was significantly associated with reductions in criminal justice involvement. However, stable employment had either no effect, or a small significant positive effect, on the likelihood of reoffending. Job quality was not associated with self-reported criminal activity at any point, in contrast to previous research (Uggen, 1999; van der Geest et al., 2011).

The final path model results reveal that, contrary to the original conceptual model (Figure 2.2), criminal activity emerged as the key explanatory variable driving men's labor force activity, financial difficulties, psychological distress, and persistence in crime. Criminal activity had a stable, persistent effect on later labor force and criminal activity, diminishing the odds that men remained employed during subsequent interview periods and increasing the odds that they persisted in criminal activity. Men who remained engaged in criminal activity experienced heightened financial need and emotional reactivity, and they were less involved in the labor force than were men who reported no criminal activity. In sum, the results suggest that, among active offenders with extensive criminal records, the path from crime does not begin with employment (van der Geest et al., 2011), but rather, the paths to employment and financial stability begin with desistance from crime (Skardhamar & Savolainen, 2014).

5.1.1 Identifying Selection Processes into Treatment

The pre-matching statistics revealed significant differences between men in the sample who engaged in educational, vocational or job training programs and men who had not received these services while imprisoned. When programs targeted to high-risk prisoners successfully recruit a high-risk treatment group, it can be difficult to locate nonparticipants in the prison who can form an appropriate comparison sample (Braga, Piehl, & Hureau, 2009; Peters, Hochstetler, DeLisi, & Kuo, 2015). Initial SVORI evaluations included propensity score weights that accounted for differences between SVORI participants and nonparticipants (e.g., enrollment in SVORI-funded reentry services) (Lattimore et al., 2012; Lattimore & Steffey, 2009). When applied to models that evaluated the effectiveness of employment programs (Lattimore et al., 2012), these weights did not adequately reduce observed differences between employment program participants and nonparticipants. As a result, initial evaluations concluded that educational programs benefited individuals who received those services, but that employment programs had detrimental effects on participants' subsequent labor force and criminal activity (Lattimore et al., 2012).

In the absence of randomization, observed treatment effects are subject to bias due to selection into treatment (D. B. Wilson et al., 2000). Selection processes commonly favor individuals who are predisposed to benefit from the treatment, as these individuals are often the most interested in and motivated to receive the treatment (Davis et al., 2013). In the case of the programs evaluated in this study, however, the factors that selected men into treatment favored men who exhibited greater service needs. These pre-existing deficits (e.g., high school dropout, low educational attainment, and limited work experience) suggest that enrollment in prison-based educational and employment services identifies individuals who entered prison with the most serious human capital deficits (Harlow, 2003). This selection process is troubling because low educational attainment and limited work experience are causally related to the primary outcomes of interest in evaluations of prison-based education and employment programs: post-release labor force participation, reoffending, and recidivism (Bushway & Apel, 2012; Duwe, 2012; Latessa, 2012).

As a result, this study contributes to the literature on prison-based programming (Bushway, 2003; Bushway & Apel, 2012). It shows that selection into some forms of prison programming reflects heightened need (Peters et al., 2015). However, it is more likely that nonparticipants in this sample were able to select out of the treatment under study (i.e., programs providing remedial education and job skills training), than that participants voluntarily opted to attend educational and employment programs (Chamberlain, 2012; Heckman & Hotz, 1989).

The literature on prison programming provides evidence to support this conclusion (Brewster & Sharp, 2002; Chamberlain, 2012; Harlow, 2003; Steurer et al., 2001). In many prisons, GED classes are mandatory for all prisoners with less than a high school education (Duwe & Clark, 2014), so these classes are composed predominantly of men who are compelled to enroll in these services in place of other alternatives (Heckman, Humphries, & Mader, 2011). Furthermore, enrollment does not equate to regular attendance, let alone consistent attention and engagement. In many cases, remedial education, job readiness, and GED programs function as silos that contain the neediest prisoners, but which are not designed to deliver the intensive support needed for these participants (Bushway, 2003). Finally, enrollees in these services are unlikely to show responsivity to the treatment, given the compulsory nature of enrollment, limited ability to compel participant engagement, and limited ability to individualize content to participants' needs (Andrews & Bonta, 2010).

In contrast, high school graduates, GED holders, and prisoners who have acquired sufficient work experience before prison may be directed away from remedial education and job training programs toward services that address other challenges these individuals may face, such as substance abuse treatment or cognitive behavioral therapy. Certain prison programs, such as the popular Puppies for Parole dog-training programs, include stringent enrollment criteria that restrict participation to the most successful, model prisoners. Prisoners are often aware of which programs available to them are viewed most favorably by prison staff and parole boards (Brewster & Sharp, 2002; Steurer et al., 2001). In this case, selection out of education and employment programs may in fact reflect selection into other programs among prisoners most equipped to succeed upon release.

To some extent, this explanation remains speculative because men in this sample did not indicate whether they were voluntary or mandatory enrollees. However, men who were imprisoned in states that used mandatory enrollment into SVORI-funded services were more likely to report educational or employment service receipt.

5.1.2 Balancing across Trajectory Groups

The propensity score matching process deviated from the proposed method in permitting matches across trajectory groups. It is worth examining why matching across groups reduced observed biases, and whether this modification casts doubt first, on the validity of the latent groups, and second, on the quality of the matches.

The retained trajectory model included observations on arrests over a 14-year period preceding the SVORI prison entry. Models that used shorter pre-SVORI observation periods (i.e., fewer than 10 years), yielded two latent trajectory groups: a high-rate group and a low-rate group. The high-rate groups derived from these 2-group models consisted of nearly all of the men assigned to Groups 1 and 3 of the final 3-group model, whereas men in Group 2 populated most of the low-rate groups in the 2-group models. A small proportion of the sample changed group membership when trajectory models used shorter observation periods: Men shifted from low-rate groups in 2-group models to the chronic offending group (group 3) of the 3-group model, and conversely from the chronic offending group (group 3) of the 3-group model to the low-rate groups in the 2-group models.

The stability in the pattern of these results suggests two important points. First, as has been found in previous studies, longer observation periods yield additional latent trajectory groups. Previous studies suggest that longer observation periods yield more accurate, stable trajectory groupings, so the literature supports the retention of the 3-group model over shorter 2-group models (Eggleston et al., 2004; Nagin & Tremblay, 2005).

This leads to the second point. The main effect of the longer observation period was to distinguish Group 1 men from Group 3 men, by focusing more on the length of the criminal history than on the level of involvement during the final years leading up to prison entry. The bivariate statistics revealed many similarities between these two groups, most notably demographic and criminal risk factors. They also exhibited similar post-release arrest rates, despite significant differences in age and length of the criminal record.

The bivariate statistics do suggest that the men in Groups 1 and 3 were fundamentally different from each other in certain risk factors relevant to the study of post-release work and crime. Namely, group 1 and group 3 men appeared to be located at opposite points along the hypothesized age-crime curve, with group 1 men entering the prime years of offending and group 3 men expected to be in the process of desistance from crime. Given these groups' opposing expected trajectories upon release, it would appear to be of paramount importance to restrict matches across groups. However, the post-release arrest rates show that group 3 men were hardly on the path toward desistance from crime; in fact, these men exhibited increased hazard rates of rearrest. Across models, there is ample evidence to suggest that men in Group 3 remained persistently high-risk and marginalized, relative to men in Groups 1 and 2. As a result, the trajectory groupings provide insight into the factors that led to men's SVORI imprisonment and enrollment in the sample, but there is limited reason to think that the groupings are fundamentally distinct (Nagin & Tremblay, 2005).

Furthermore, the factors selecting men into treatment did not differ substantively for men in Groups 1 and 3; men in Group 3 were less likely to receive services, but participant-nonparticipant differences were comparable across these two groups. The same is not exactly true for men in Group 2, as factors selecting men into treatment for this group were not exactly identical to those for the other groups.

In this case, the use of the group-based trajectory modeling complemented the propensity score matching process and appeared to improve the overall quality of the matches. At the very least, the group-based trajectory model provided an efficient way to capture distinct pre-prison arrest trajectories. The dummy variables for group membership (and related interaction terms with age, education, and prison term) captured relevant differences among groups across multiple domains.

5.1.3 Maintenance of the Status Quo

Viewed as a whole, the significant coefficients in the duration models in this study provide evidence to suggest that risk factors for rearrest reflect stable characteristics that existed before men entered prison (Duwe, 2012; Horney et al., 1995). The significant positive coefficients in the repeated-events duration model reflect stable criminal risk factors (e.g., previous prison terms, violation of supervision); ongoing factors correlated with criminal activity (recent alcohol or drug use), and structural factors that influence the likelihood and timing of rearrest (state location, racial/ethnic status).

The significant negative coefficients for longest job tenure before prison and length of the SVORI prison term suggest that maturational reform may account for differences in time to rearrest. Men who had maintained jobs for longer periods before prison were less likely to be rearrested than were men who had never worked or had only held jobs briefly before entering prison. Similarly, longer prison terms were associated with reduced odds of rearrest. As age did not influence the likelihood and timing of rearrest, it appears likely that job tenure and prison term partially reflect the effect of aging out of crime. However, if maturational reform does account for delays in rearrest among men who had previously held stable employment, then it is clear that the process toward desistance had been underway prior to entering prison.

5.1.4 Understanding Why Employment Programs do not Work

The results generally show that men continue to engage in fundamentally the same behaviors that they had exhibited prior to entering prison. From this perspective, it is easy to understand why prison-based education and employment programs often have limited success in improving men's labor force outcomes. To use educational programming as an example, Adult Basic Education and GED programs cover the same content that is covered in secondary schools, and the teaching methods used replicate the traditional lecture-based classroom environments common among American high schools. The high school dropouts enrolled in these programs have essentially received, and not been responsive to, the educational treatment offered, so there is limited reason to think that the programs will have a significant effect on their behavior. To yield improved outcomes, the teaching methods used in remedial and GED programs may need to undergo significant revisions to address participants' specific needs and learning styles (Andrews & Bonta, 2010).

Risk-Need-Responsivity Framework

Programs that target individuals with the highest risks of reoffending offer the potential for the greatest returns on investment, in terms of reduced crime, victimization, and correctional costs (Braga et al., 2009; Peters et al., 2015; Zweig et al., 2011). Zweig and colleagues (2011) reanalyzed outcome data from the Center for Employment Opportunities (CEO), a subsidized jobs program serving former prisoners in New York City. When the authors categorized participants by risk of recidivism, they found that high-risk participants were most responsive to the intervention (reducing the probability of arrests and convictions, and the frequency of arrests, among high-risk participants). Participation had no corresponding effects on the low- and medium-risk participants (Zweig et al., 2011).

Older studies provided partial support for job training and vocational programs (Saylor & Gaes, 1997; D. B. Wilson et al., 2000), but methodological weaknesses in some studies suggest that observed benefits result from selection into treatment (Brewster & Sharp, 2002). Current studies suggest that it is not the employment readiness or job training components of these programs that reduce recidivism risk (Jacobs, 2012; Redcross et al., 2012; Zweig et al., 2011). In the case of the CEO program noted above, the high-risk participants were no more likely to locate unsubsidized employment than were the high-risk nonparticipants, so other programmatic factors appear responsible for the recidivism reductions among the high-risk subgroup (Zweig et al., 2011).

Intervention components that appear to reduce criminogenic risk factors include chemical dependency treatment (Peters et al., 2015), mentorship (Braga et al., 2009; Redcross et al., 2012; Zweig et al., 2011), case management (Braga et al., 2009; Zweig et al., 2011), and postsecondary education (Duwe & Clark, 2014; Kim & Clark, 2013; D. B. Wilson et al., 2000). Interventions that include therapeutic components and apply cognitive behavioral and social learning techniques exhibit improved outcomes over programs that lack this therapeutic focus (Andrews & Bonta, 2010).

Weak Program Design and Implementation

The weak effects of education and employment programs in this study may have resulted from variations in the quality and intensity of services offered by each state (Andrews & Bonta, 2010; Lowenkamp, Latessa, & Smith, 2006; Peters et al., 2015). Unfortunately, the SVORI evaluation lacked the administrative data needed to evaluate whether some states provided higher quality programs than other states did. As a result, it is difficult to assess whether null findings reflect poor program design, mismatch to participants' needs, or poor delivery (Bouffard, Taxman, & Silverman, 2003; Lowenkamp et al., 2006; Peters et al., 2015; J. A. Wilson & Zozula, 2012).

Demonstration projects often yield much larger effect sizes than do comparable interventions that are applied rigorously in correctional settings, suggesting that correctional systems face logistical challenges in scaling up effective programs (Andrews & Bonta, 2010). Prison administrators in the SVORI evaluation overestimated the extent to which prisoners had received services before release from prison (Lattimore, Visher, & Steffey, 2011), and it is quite possible that they overestimated how quickly they would be able to scale up existing programs or introduce new services. Some states had limited existing reentry services in place for prisoners, so correctional staff in these sites faced the additional hurdle of developing programs for SVORI participants. States with existing services in place could focus their efforts on increasing access to a greater range of services (Lattimore et al., 2011).

Failure to obtain buy-in from correctional staff may have hindered the effective delivery of services to education and employment participants (Bonta, Rugge, Scott, Bourgon, & Yessine, 2008; Lowenkamp et al., 2006; Van Voorhis, Cullen, & Applegate, 1995). Staff may recruit ineligible people into the treatment group, provide services to comparison group members, and/or modify components of the intervention based on staff members' perception of how the program should work (Peters et al., 2015). The institutional culture in some prisons emphasizes security and control over rehabilitative programming (Bushway, 2003), so newly designed programs may have contradicted or challenged existing correctional procedures, leading administrators to abandon essential components of the reentry model. Logistical challenges often hamper participation, as when participants transfer abruptly to other correctional institutions or leave prison at the completion of their sentence (Bushway, 2003; Steurer et al., 2001).

Evaluators rarely conduct process evaluations during the early stages of an intervention, to ensure that the program is being implemented as designed. Process evaluations may require that prison staff collect data on program components that previously went unmeasured by prison staff, including detailed information on program attendance, content, participant engagement, and completion (Bouffard et al., 2003; Lattimore et al., 2011; Steurer et al., 2001). If these data collection procedures are not integrated into existing tasks, prison staff may fail to collect data consistently and reliably (Bouffard et al., 2003).

Work Doesn't Work, and Perhaps It Never Did

If employment programs are going to be evaluated by their ability to reduce recidivism, the literature suggests that employment services may need to be wrapped around the primary intervention (e.g., chemical dependency treatment, postsecondary education) (Duwe & Clark, 2014; Kim & Clark, 2013; Peters et al., 2015). Observational data suggest that employment has, at best, a weak causal effect on crime, so the potential benefits of even the strongest prison-based employment program will be modest (Bushway, 2011; Farabee et al., 2014). Programs that successfully increase participants' labor force attachment may reduce overall recidivism rates, but the observed reductions may be too small to be of statistical, let alone practical, significance (Bushway & Apel, 2012; Lattimore, Steffey, & Visher, 2010).

Lattimore, Steffey, and Visher (2010) present the following example of an employment program that boosts participants' employment rate by 20% (to 60% from the baseline 50% rate for nonparticipants). By helping participants gain employment, the intervention reduces their rate of criminal involvement by 20% as well (to 40%, from the 50% baseline rate). However, these sizable improvements may have only a small effect on rearrests, if the 20% reduction in reoffending manifests as 1 fewer arrest per 100 participants (2.2% reduction in recidivism) (Bushway & Apel, 2012). Indirect interventions, such as the one described by Lattimore and colleagues (2010), may be more equipped to show their effectiveness by incorporating proximal outcomes (e.g., skills gained, attitudinal changes, job search activities) that plausibly link program completion to the key, often distal, outcomes (e.g., labor force participation, reoffending) (Bushway & Apel, 2012; Farabee et al., 2014). Given the relative lack of support for employment programs as currently provided, evaluations that assess whether programs actually improve participants' hard and soft skills, prior to release from prison, could provide preliminary evidence to support programs that otherwise show limited effects on post-release work and crime.

Weak Signals

The negligible observed effects of education and employment programming may have resulted from the inability to identify men in the SVORI evaluation who completed programs and/or received credentials while imprisoned (Bushway & Apel, 2012; Lowenkamp et al., 2006). Successful completion of certain degree programs confers on graduates a credential that may improve their employment prospects (Duwe & Clark, 2014). Completion status provides useful information for evaluators as well; in many cases, unobserved risk factors influence the likelihood of completing the program and of reoffending (Bushway & Apel, 2012; Miller, 2014; Peters et al., 2015). Even where program designers believe that the program will improve outcomes, regardless of completion status, knowledge of which participants achieve the credential can be used to minimize unobserved variable bias (Peters et al., 2015).

Postsecondary education completion appears to provide the most useful credential for reentering former prisoners (Brown, 2015; Duwe & Clark, 2014), but this option appears to have been out of reach for most men in the SVORI evaluation. Education participants may not have been academically prepared for college classes, as four in ten men had less than a high school education at release from prison. Furthermore, only a minority of them likely resided in prisons that offered post-secondary education. As of 2015, only 6 of the 11 states provided degreegranting college education programs to select groups of individuals (Prison Studies Project, 2015).

In the case of prisoners enrolled in GED programs, it is unclear whether passing the GED test actually provides a useful credential upon release (Heckman & LaFontaine, 2006; Heckman & Rubinstein, 2001; Tyler, Murnane, & Willett, 2000). Among a sample of Minnesota state prisoners, completing post-secondary education in prison significantly reduced the odds of rearrest, reconviction, and return to prison (Duwe & Clark, 2014). Completing the GED or high school diploma while imprisoned had no effect on recidivism outcomes (Duwe & Clark, 2014). Other studies suggest that, absent pursuit of further education, GED completion does little to improve labor force outcomes for GED holders, relative to high school dropouts (Brown, 2015; Heckman et al., 2011).

From the perspective of potential employers, the GED credential may not offset former prisoners' negative credentials: their criminal records, removal from the labor market, and lingering human capital deficits (Brown, 2015; Miller, 2014; Tyler & Kling, 2007; Tyler et al., 2000). Holding a GED may even hinder employment prospects for some former prisoners, based on comparisons among high school dropouts, GED graduates, and high school graduates. Based on tests of cognitive ability, such as the Armed Forces Qualifying Test (AFQT), GED graduates appear to be as intelligent as high school graduates who do not attend college, and more intelligent than high school dropouts who do not obtain GED certification . However, when controlling for cognitive skills and number of years in school (before dropout), GED holders actually experience greater job instability, earn lower hourly wages, and accumulate less work experience over time than do uncredentialed high school dropouts. These patterns hold even when samples exclude former prisoners (Heckman & Rubinstein, 2001).

The paradoxical findings for GED completion suggest that noncognitive factors, such as internal locus of control, self-esteem, and sociability, adversely differentiate GED holders from both high school dropouts and high school graduates (Heckman & Rubinstein, 2001; Heckman et al., 2006). Low-skill job markets prioritize noncognitive skills over cognitive skills, in contrast to high-skill job markets, which value the latter over the former (Heckman et al., 2006). Lacking postsecondary education or trade certification, GED holders remain unqualified for high-skilled jobs, for which their low noncognitive skills would present less of a liability. However, in attaining the GED credential, GED holders differentiate themselves from uncredentialed high school dropouts, and this may explain GED holders' disadvantaged position in the formal labor market (Heckman & Rubinstein, 2001; Heckman et al., 2006).

5.1.5 Structural Factors Trump Human Capital Factors

Social structures (e.g., racial/ethnic status, state of residence) appear to have stronger effects on arrest outcomes among this sample than theoretically relevant predictors do, such as age and level of education. When racial/ethnic status and SVORI site were excluded from the nested duration models, higher levels of educational attainment increased the time that men remained in the community before rearrest. Further education was no longer significantly associated with rearrest when racial/ethnic status and state of residence were included in the model. These findings may reflect state-level differences in arrest rates; it is not clear to what extent higher rates of arrests among African Americans are the result of racial profiling or similar justice practices (see Figures 4.1-4.6 for graphs of pre-SVORI arrest rates by racial/ethnic status; Tables 4.8 and 4.9 for duration model results).

Racial/Ethnic Differences in Rates of Offending and Arrest

Disproportionate minority involvement in the criminal justice system likely reflects real differences in levels of policing, prosecutorial discretion, and criminal justice sanctioning, especially for less serious crimes that may go unreported or unobserved by police (the "differential criminal justice system selection hypothesis") (Piquero & Brame, 2008). However, racial/ethnic differences in arrest rates may also reflect differential rates of involvement, if minorities are more likely to remain involved in criminal activity over the life course (the "differential involvement hypothesis") (Anderson, 1999; D'Alessio & Stolzenberg, 2003; McNulty & Bellair, 2003; Piquero & Brame, 2008).

Between these two divergent perspectives, a middle position exists, which hypothesizes that police and criminal justice processes discriminate against minorities, but that individual, social, and structural factors contribute to higher rates of serious crime among minorities (Piquero & Brame, 2008; Piquero, MacDonald, & Parker, 2002). For instance, racial differences between African American and White male former prisoners in timing to first violent felony disappeared when controlling for local unemployment rate and access to manufacturing jobs (Bellair & Kowalski, 2011). The association between unemployment and violent offending has also been observed among African American prisoners in Florida; for these men, rising African American unemployment increased the likelihood of a new felony offense within 2 years of release (Mears, Wang, & Bales, 2014).

The results of studies using self-reported information often differ from studies that use official records, which consistently show higher arrest rates among African Americans and other minorities than among Whites (Piquero & Brame, 2008). Ideally, self-report measures would provide insight into the source of the racial disparities in criminal justice involvement.

Unfortunately, older studies that have collected official records and self-reported information on official records revealed significant differences by racial/ethnic status in the accuracy of self-reported information (Farrington, Stouthamer-Loeber, Van-Kammen, & Schmidt, 1996; Hindelang, Hirschi, & Weis, 1981; Huizinga & Elliott, 1986). These original studies often used adolescent samples that engaged in less serious forms of delinquent behavior, so the results may not generalize to adult prisoners with extensive criminal records (Piquero & Brame, 2008). Recent studies have provided mixed evidence to support the validity of self-report measures (Jolliffe et al., 2003; Maxfield, Luntz Weiler, & Spatz Widom, 2000; Piquero & Brame, 2008; Piquero, Schubert, & Brame, 2014; Sampson, Morenoff, & Raudenbush, 2005).

State-Level Differences in Arrest Rates

The duration and path models revealed significant differences in the odds of arrest by state location. These differences likely reflect differential rates of criminal activity by individuals within each state, although multiple potential sources of variation also exist at the local and state levels. First, policing practices vary across localities and states, which in turn influence the likelihood and timing of arrest. Second, prosecutorial discretion at the local level influences the odds that an arrest leads to prosecution, conviction, and eventually imprisonment. The length of time imprisoned for a given offense varies across states, as do prison conditions and access to programming within prisons.

State recidivism rates reflect the cumulative impact of these local and statewide variations in criminal justice practices, rendering it difficult to compare outcomes across states. In the case of the repeated-events duration model, residents from two states (Maryland and Washington) showed large increases in the baseline hazard of rearrest. Recidivism rates for these two states were the second- and third-highest rates, respectively, of the 11 states included in the duration models (Pew Center on the States, 2011; Rosenwald, 2011). The reduced time to first arrest for Maryland and Washington prisoners therefore reflects, in part, the policing or supervision practices in these states.

Finally, states appeared to recruit participants into the SVORI evaluation using different aspects of the SVORI enrollment criteria. Several states enrolled high proportions of men with recent drug convictions, most notably Iowa (58%) and Maryland (66%). Property offenders frequently exhibit the highest rates of rearrest and return to prison, relative to drug and property offenders, but none of the states appeared to use property convictions as criteria for enrollment into the SVORI evaluation (Lattimore & Steffey, 2009).

States that enrolled the highest proportions of violent offenders included Kansas (61%), Nevada (88%), Ohio (58%), and Washington (65%). Violent offenders often exhibit the lowest recidivism rates, in comparison to drug and property offenders. This is born out for Nevada, which had the lowest statewide recidivism rate in 2004, of the states in the sample (Sentencing Project, 2010).

However, in the case of Washington State, the enrollment criteria were designed to recruit a high-risk, high-needs sample (e.g., under 35 years old and fitting one or more categories reflecting heightened risk or needs). Men from Washington State who fit these criteria and were selected for the SVORI intervention were then mandated to receive services (Lattimore & Steffey, 2009). The LSEM results showed that men from Washington State were significantly more likely to have reoffended within each 6-month reference period, so policing practices do not fully account for state-level differences in rearrest.

5.1.6 Limited Support for Causal Theories of Work and Crime

The LSEM results generally refute the turning point hypothesis outlined in Section 1.1.3, but it is not clear to what extent the findings may be interpreted as supporting maturational reform in place of the hook-for-change hypothesis (Giordano et al., 2002; Laub & Sampson, 2001; Skardhamar & Savolainen, 2014). Employment did not reduce the odds of later offending, suggesting that the jobs attained by prisoners in this sample lacked the requisite qualities needed to foster social bonds and reduce criminal activity (Laub & Sampson, 2001). The fact that stable employment never reduced the odds of subsequent criminal activity (in fact, it predicted *higher* odds of committing crime during the last interview wave) appears to suggest that maturational reform had not yet taken place among men in this sample. The results do leave open the possibility that stable employment could have provided the hooks-for-change needed to support men's path toward desistance, had men in this sample expressed (implicitly or explicitly) intentions to "go straight" (Skardhamar & Savolainen, 2014).

Results from a longitudinal study that followed work and offending trajectories during early adulthood among a sample of former juvenile delinquents provide a possible explanation for stable employment's negligible effects on crime in the LSEM. Among high-frequency offenders in the sample, stable employment had no effect on convictions during the same 1-year period (van der Geest et al., 2011). In a separate study that examined the timing of employment and reoffending for a sample of serious offenders, steep declines in criminal activity preceded employment spells for most men in the sample (Skardhamar & Savolainen, 2014). The delay between prior offense and most entries into stable employment (lasting at least 6 months) was extensive, spanning 2 years or more, lending credence to the conclusion that desistance precedes stable employment (Skardhamar & Savolainen, 2014).

5.1.7 Testing Theoretical Concepts

Strength of Weak Ties

Results of this study support human and social capital theories of work and crime. Odds of maintaining stable employment, and resisting criminal activity, were higher among men who reported social networks comprising higher proportions of employed and prosocial peers. The opposite pattern emerged when items measuring time spent with employed and prosocial peers were included in the model: Socializing with peers, even those who were employed and likely to help men avoid trouble, reduced the odds that men maintained employment, and increased their odds of reoffending.

Findings from a recent study examining parolees' job search activities and emotional wellbeing during the first 90 days of release provide insight into the role of social networks (Sugie, 2014). As theorized by human and social capital theories, men who expanded their social networks during the reentry period enjoyed greater success in finding work, and of finding work paying more than a minimum wage. However, men who felt close to people in their post-release social network spent more time unemployed. Strong ties to contacts also extended the time until men located formal labor market employment and jobs paying more than the minimum wage (Sugie, 2014). Men who felt strong ties to people in their social network had likely maintained contact with people they had known before entering prison, and these existing peer networks may not have facilitated men's connections to the labor market. Overall, the results suggest the importance of weak ties (Granovetter, 1973), and the potential importance of replacing past peer networks with new, possibly more prosocial peer networks (Hagan, 1993).

Managing Financial Needs During the Reentry Period

Results of this study suggest that greater focus should be paid to the financial and psychological consequences of remaining engaged in criminal activity (Bucklen & Zajac, 2009; Felson et al., 2012). When controlling for men's prior levels of psychological distress, prior labor force activity, and peer support networks, self-reported recent criminal activity was associated with concurrent unmet financial needs and psychological distress. However, remaining engaged in the labor force, or even finding higher-quality employment, had limited effects on men's feelings of financial and emotional wellbeing. For men in this sample, consistent employment led to improved job quality, and higher quality jobs diminished men's financial needs, but there were no reciprocal paths leading from financial need or psychological distress to later labor force and criminal activity.

Heightened financial need among men who persisted in criminal activity may reflect a shortsighted inability, or lack of interest, in taking control of their finances. In a study that examined factors influencing parolee success, Bucklen and Zajac (2009) observed that financial management and coping strategies differentiated parole violators from parole successes (those who had no parole violations or returns to prison during the first 3 years of release). Individuals who eventually violated parole or returned to prison perceived significantly greater financial difficulties than did parole successes, even though median debt levels were much lower among parole violators than among parole successes.

5.1.8 Fostering Desistance among Former Prisoners

The LSEM results provide limited evidence to suggest that men can work themselves into desistance from crime. Previous sections in this chapter have noted the path dependent nature of men's post-release activities, which can be seen most clearly in the duration models, yet also seems present in the path model results. Men in the sample had been involved in criminal activity before entering prison, and many of them resumed quickly upon release. Similarly, unstable unemployment characterized the majority of men's labor force activity during the months leading up to and following release from prison.

Findings from this and other recent studies refute long-standing assumptions about the crime-reducing effect of employment that had been supported by studies using data from the mid- to late-20th century (Laub & Sampson, 2001; Uggen, 2000). In previous decades, when union-protected manufacturing jobs paid good wages to men with limited education and soft skills, employment likely did reduce crime, by keeping men occupied on a regular basis and increasing their stakes in conformity (Hirschi, 1969; Laub & Sampson, 2001). Studies have shown that, even in the 21st century, postindustrial United States, former prisoners who live in areas with higher levels of manufacturing jobs have lower odds of committing new violent offenses (Mears et al., 2014). The loss of manufacturing jobs during the latter part of the 20th century has decimated the low-skilled labor market, with predictable consequences for low-educated former prisoners' long-term employability.

Even though former prisoners in the SVORI sample exhibited no signs of desisting from crime and only limited engagement with the labor force, it merits consideration whether men leaving prison in coming years will be able to find the kinds of jobs that had once provided hooks-for-change, if not also turning points, for former prisoners. It may be that these jobs simply do not exist in sufficient quantities to provide viable options for former prisoners, especially when people without criminal records are competing for the same positions.

Identity, Agency, and the Desistance Process

The relative absence of strong social factors that may foster desistance, such as high-quality employment, means that subjective, internal factors play a large role in bolstering former prisoners' intentions to "go straight" (LeBel, Burnett, Maruna, & Bushway, 2008). As a result, research on desistance from crime has increasingly focused on the personal, often private, cognitive transformations that lead former prisoners to cast former friends aside, take on previously ignored financial and personal responsibilities, and accept the inevitability of legal work as their best long-term option (Bucklen & Zajac, 2009). Desistance scholars traditionally envision personal agency as an intrinsic characteristic within individuals that shapes their behavior and ability to carry out long-range plans. In many cases, persistent offending reflects the fact that men feel they lack agency over their own behavior. Successful desisters seem better equipped than do non-desisters to perceive a credible new self, and then to marshal internal agentic forces toward pursuit of the imagined self (Healy, 2014; Maruna, 2001).

It may be possible to design reentry interventions that build upon former prisoners' inherent ability to redirect their own actions toward desired goals. Prisons have experimented with entrepreneurial training programs for prisoners, as a way to overcome the informal and formal restrictions on employment for people with felon records. Preliminary research suggests that entrepreneurship training programs have the capacity to differentiate prisoners who enter the program with the requisite "personal agency mind-set" needed for entrepreneurial success upon release (Patzelt, Williams, & Shepherd, 2014). Case studies have shown that successful completion of an entrepreneurial training program identifies prisoners who feel high levels of self-efficacy and have taken responsibility for the actions that led them to prison. For these individuals, the training program increases their orientation to the future, and this future orientation is fostered through the use of program activities that provide participants with opportunities to practice behaviors that will help them achieve their long-term goals (Patzelt et al., 2014).

5.2 Challenges and Limitations

5.2.1 Group-Based Trajectory Model

The sample is composed of men who were completing prison sentences in 11 US prison systems. Most of the men who were recruited into the sample began their prison terms months, even years, before SVORI was designed and implemented. Although two states did randomly assign men to participate in SVORI-funded programs, the other states selected their nonparticipant samples from similar sites within their states (Lattimore & Steffey, 2009). The years preceding men's release from prison varied significantly, depending on the lengths of their prison term, offense type, and characteristics about the states in which they were completing their prison terms. As a result, the use of men's pre-SVORI arrest records to identify latent trajectory groups may have ignored or minimized important state-level differences.

5.2.2 Defining Participation Status

The baseline interview provided information on services men had received during their entire SVORI-related prison terms, including services received before the design and implementation of SVORI-funded services. Men who had served longer prison terms had greater access to education and employment services, especially more intensive higher education and job training programs. The lack of administrative data, and limited detail from respondents on program participation, limits the extent to which this study can assess the quality of the services provided. The SVORI evaluation did not obtain detailed information about the intensity, content, or duration of the services men received, and men were not asked whether they had received any certification or credentials while imprisoned. Despite this, the services men received are comparable to the education and employment programs offered by most US prisons, and it is worth noting that all of the services that nonparticipants received, and perhaps most of the services received by nonparticipants, had been implemented in the absence of SVORI funding. In this respect, service receipt by the serious and violent offenders in this sample is likely representative of service receipt for comparable men in all US prisons.

5.2.3 Duration Models

The single- and repeated-event duration models use recorded dates from official arrest record files to depict failure rates following release from prison. Rearrests are distal measures of reoffending following release from prison, so duration models that included time to first self-reported offense could provide stronger evidence about the short-term effects of program participation (Davis et al., 2013).

Although the arrest records were cleaned to remove charges that preceded men's release from prison (e.g., arrests recorded on their day of release, which likely reflected pre-existing charges), it is possible that the remaining arrest records included charges that had occurred prior to men's release date.[1] It is also possible that states and local jurisdictions varied in the speed and accuracy with which they arrested individuals and recorded the arrests. Furthermore, it is not possible to assess whether the arrest records fairly reflect differences in individuals' levels of criminal activity following release. Most notably, significant differences in time to arrest by racial/ethnic status may reflect differences in crime rates by racial/ethnic status, but they also likely reflect differences in local policing, community crime rates, and state corrections systems.

[1] Defining arrests that occurred on men's first day of release (time 0) as having occurred before release resulted in differences for six matched cases. The SVORI arrest indicators code these men as having been arrested within the first 3 months of release, whereas the continuous time measures used in this study code them as never being arrested. Three of the men were participants and three were nonparticipants; none had arrests recorded after their day of release, so all six men are included in the sample as survivors during the first 3 years of release. In this sense, they were not failures in that they were never arrested following the first day of release, but it may be that their arrests led to new prison terms that prevented them from returning to the community during the 3-year period.

5.2.4 Structural Equation Modeling

Measures

***Labor force participation*.** The main results of this study operationalize labor force participation as stable employment, in which men worked each month that they were living in the community. The general findings are supported when labor force participation is defined as a continuous measure (proportion of months working) or categorical measure (none, some, or all months working). However, the variable numbers of months in which men were living in the community between interview periods may render these items less reliable than if men had been in the community for the same lengths of time. It was also not possible to distinguish between men who worked only once within a given month from men who worked consistently throughout the month. The descriptive statistics indicate that when even this weak measure for stable employment was used, less than 1/3 of respondents at each wave met the criteria.

***Job quality*.** The CFA and LSEM included two scaled items for job quality. The items measure features about respondents' most recent jobs, whether they were currently employed or not: hours worked during the average week and attributes of primary sector employment (van der Geest et al., 2011). Other studies have measured job quality using mean job satisfaction scores that reflect the objective desirability of given occupations (Uggen, 1999). The continuous hourly wage items at each wave were not reliably measured and showed weak associations with the other items and the latent factor for job quality.

Financial needs. This study hypothesized that financial strain was the key concept linking employment to criminal activity. By reducing financial difficulties and the resulting psychological distress that men experienced, stable employment would reduce the odds that men persisted in criminal activity. Studies traditionally define financial strain by individuals' self-reported inabilities to afford basic goods and necessities in the present, and the extent to which they anticipate financial constraints in the future. In contrast, the measures available from the SVORI interviews indicate respondents' self-assessed need for assistance in obtaining basic goods and services.

It is possible that men's responses would have been different if the questions had focused on men's ability to obtain goods and services on their own (or with the help of their family), not on men's need for assistance. Furthermore, the six financial needs items used in this study were selected from a list of approximately 25 items that measured a range of service needs, from legal assistance to anger management counseling. When answering these questions, men may have considered their financial needs relative to other non-financial needs they may have had.

Psychological distress. The 15 psychological distress items did not fit strongly on one latent factor, nor did items within subscales load unidimensionally on their own factors. In most instances, the 5-level items approximated binary indicators, with most respondents reporting no experiences of each symptom within the previous 7 days. As a result, the CFAs fit using the 15 original ordinal items showed poor fit, with only one or two items loading strongly on the latent factor. Due to low cell counts for the top three categories within each item (especially for the hostility indicators), new 3-level variables were created that collapsed these most serious responses into one category. These new items also showed poor model fit when modeled as ordinal-level items.

It is not clear whether the poor fit resulted from the use of a 7-day window, the phrasing of the items and range of response options, or from sensitivity about the concepts being measured. Research suggests that questions about general mental health overestimate the extent to which former prisoners experience psychological distress, and underestimate the extent to which they experience positive emotional states (Sugie, 2014). The use of interview items capturing negative emotional states may not provide accurate measures of men's general emotional wellbeing.

It is also possible that the psychological distress items used in this study did not in fact measure emotional states resulting from prior financial need and criminal involvement. Instead, these parceled items may reflect individuals' emotional reactivity, which in turn influenced their financial wellbeing and likelihood to engage in crime. Nonetheless, the theoretical significance of psychological distress, or emotional reactivity, drives home the need to validate indicators of psychological functioning for use in large-scale prisoner studies.

Crime. The binary measures for any type of criminal involvement since the previous interview limited the extent to which one can differentiate individuals who remained persistently engaged in crime from those who had only offended once or twice since release. Indicators for specific type of crimes committed, most notably property offenses, may have yielded significant results for stable employment, as previous studies have found property offending to be associated with unemployment and financial strain (Aaltonen et al., 2013; Felson et al., 2012). It was also not possible to assess whether men answered the questions honestly, although men were often forthcoming about illicit substance use and illicit earnings at each wave.

Results for criminal justice involvement show divergent results from findings for self-reported criminal activity; this may reflect policing patterns or may reflect differences in the severity of offenses committed. Previous research has suggested that racial/ethnic differences exist in the validity of self-report delinquency and crime measures (Farrington et al., 1996; Hindelang et al., 1981; Huizinga & Elliott, 1986). Recent studies provide contradictory evidence for invariance by racial/ethnic status in the accuracy of self-report crime measures, especially among adult and high-rate offender samples (Piquero et al., 2014). The results of this study may reflect the same general pattern of African American males underreporting criminal activity, albeit among adult male former prisoners. However, the results may reveal real differences by racial/ethnic status in the association between crime and arrest.

Temporal ordering

The LSEM used a cross-lagged design, in which work and crime status were regressed on work and crime status during the next 6-month period. This may not be the appropriate time lag for either concept; the paths for employment status at Wave 2 to both work and crime at Wave 4 were not significant, so the effect of work may be short-lived. For instance, van der Geest and colleagues (2011) observed that the effect of employment on offending among high frequency, chronic offenders was instantaneous, with limited enduring effects. The 3- to 6-month lag between employment status and crime used in this study may have been too long to capture short-term changes in criminal activity that results from changes in employment status.

In contrast, early criminal involvement at Wave 2 remained significant at Wave 4, even when controlling for Wave 3 crime and other predictors. Future research should use monthly measures to assess whether the findings of this study hold when shorter lag periods are used.

Most of the paths in the LSEM specified directions from the preceding to current waves. The phrasing of the questions at each follow-up interview informed the selection of paths from crime to financial need, crime to psychological distress, and financial need to psychological distress. It is possible that men's psychological distress over the preceding 7 days was a fair representation of their psychological wellbeing over a longer period. If that is the case, the path from crime to psychological distress is misspecified. It is also possible that current financial need had actually preceded criminal involvement during the same interview reference period. However, it is not possible to make that assumption, due to the phrasing of the questions.

Chapter 6: Implications and Conclusion

6.1 Implications for Policy

6.1.1 Logic Models and Program Evaluations

The logic models underpinning most prison- and community-based employment programs link employment services to increased labor force activity and reductions in criminal activity (Farabee et al., 2014; Redcross et al., 2012). Theoretical models commonly suggest that increased labor force participation reduces men's involvement in criminal activity, but mounting empirical evidence suggests that this association may be unfounded. At the very least, it appears to be too optimistic (Hagan, 1993; Horney et al., 1995; Skardhamar & Savolainen, 2014). The results of this study emphasize the need to unlink recidivism outcomes from employment program evaluations (Bushway & Apel, 2012; Redcross et al., 2012).

Current employment programs rely on cost-reductions in crime and criminal justice involvement to justify investments in employment training and assistance, so decoupling recidivism reductions from program completion may complicate efforts to sustain funding for employment programs. Including proximal measures that capture the intermediate effects of program participation (e.g., attitudinal changes, cognitive gains, and job-seeking strategies) would increase our understanding of how successful education and employment programs influence the odds of later employment and crime. Including these short-term outcomes in evaluations could help identify subgroups that are the most responsive to programming (Davis et al., 2013).

6.1.2 Policy Changes to Improve Correctional Programming

Evaluations should apply the Risk-Need-Responsivity (RNR) framework to the design, implementation, and evaluation of correctional programs (Latessa, 2012; J. A. Wilson & Zozula, 2012). A growing body of evidence suggests that weak labor force attachment among former prisoners reflects low levels of noncognitive skills more than the lack of cognitive ability (Heckman & Rubinstein, 2001; Heckman et al., 2006; Lindqvist & Vestman, 2011). Low-skill job markets prioritize noncognitive skills over cognitive abilities, an imbalance that leaves many young, male former prisoners at a disadvantage when seeking employment. Employment programs may need to be designed to emphasize the development of soft skills (e.g., noncognitive skills) while providing participants with opportunities to complete their education or achieve job-training credentials (Heckman & Rubinstein, 2001; Lindqvist & Vestman, 2011; Miller, 2014).

Correctional education programs may not be able to shift focus away from GED preparation, given the high rates of prisoners with less than a high school education (Harlow, 2003; Heckman et al., 2011). However, the literature shows that helping prisoners obtain the GED credential alone is not sufficient to improve their reentry prospects (Brown, 2015; Heckman et al., 2011; Tyler & Kling, 2007). Removing the restriction on Pell Grants for former prisoners would increase the provision of postsecondary education programs in state prisons (Batiuk, Lahm, Mckeever, Wilcox, & Wilcox, 2005; Brown, 2015). College degrees appear to diminish the stigma associated with the criminal record, perhaps due to the shift in emphasis from noncognitive to cognitive skills in high-skill job markets (Heckman et al., 2006).

6.1.3 Policy Changes to Increase Labor Force Attachment

Removing employment restrictions that are not justified by public safety interests would help former prisoners find stable employment providing a living wage. Subsidized insurance and tax credits for employers who hire former prisoners would increase employers' willingness to consider applicants with felon records. These incentives would have fewer unintended consequences than policies that limit employers' access to applicants' criminal records. In the absence of complete knowledge about applicants' criminal backgrounds, employers already look for markers to identify former felons, and these markers lead employers to discriminate against young, minority men. This would likely increase if employers knew that they were legislatively barred from learning about applicants' criminal risk.

Correctional departments should develop systems, in partnership with local service agencies, to share information about reentering prisoners' job skills, program participation, and talents with potential employers. This positive information could help offset information about prisoners' criminal records that limit employers' willingness to hire them.

6.2 Implications for Future Research

6.2.1 Improving Research Designs using Observational Data

Recent meta-analyses show that prison-based postsecondary education programs do reduce recidivism rates, so it is not clear why education programs did not have any long-term effects on participants' ability to maintain employment or reduce criminal involvement (Davis et al., 2013; Duwe & Clark, 2014). Null findings may reveal ineffective programs, but they may also reflect low rates of participation among men receiving education and employment services. Future research should examine program dosage, in terms of program intensity, duration, content, and delivery method (Davis et al., 2013; Steurer et al., 2001). Existing studies have not consistently differentiated education programs by type, so it is not clear whether some types of correctional education yield more benefits than others (Steurer et al., 2001).

Regression Discontinuity

This study used propensity score weighting to balance participants and nonparticipants, but this method only reduces observed heterogeneity. Regression discontinuity designs can diminish observed and unobserved heterogeneity, thereby increasing the methodological rigor of future program evaluations. To implement a regression discontinuity design, evaluators must have access to a continuous measure, such as Tests of Basic Adult Education (TABE), that reliably measures individuals' latent ability. Evaluators then use a cut-point to assign respondents to the treatment and comparison groups; scores that fall above the cut-point are included in the treatment group and scores that fall above the cut-point are assigned to the comparison group. If there is a linear association between latent ability (as measured by the continuous scale) and the observed outcome, then the difference in outcomes for sample members above and below the cut-point should reflect the true effect of the program (Davis et al., 2013).

Successful regression discontinuity designs may entail more planning during the research design stage than do some propensity score methods, which can be implemented successfully at the analysis stage. It can be difficult to find an appropriate continuous variable in administrative records, so program evaluators may need to modify the sample selection process to include testing. The internal validity of this method is reduced when program implementers violate the assignment rule, so it is critical that practitioners faithfully apply the rule when assigning participation status. Furthermore, poorly implemented or designed programs may not meet the linearity assumption (Davis et al., 2013).

Use of Smartphones to Collect Data

Recent studies have experimented with the use of text messaging to collect data from respondents on a more frequent basis (Gaggioli et al., 2013; Sugie, 2014). This technique has been successfully implemented in a study following parolees during the first 3 months of release from prison (Sugie, 2014). Compared to men who were assigned to the traditional interview condition, men assigned to the smartphone condition were more likely to agree to participate in the study (89% vs. 68%) and to remain involved in the project throughout the 3-month study period (Sugie, 2014).[1] The completion rate for men who entered the study (82%) is higher than has been observed in other longitudinal studies following prisoners after release, including the SVORI evaluation (58% completion rate for the 3-month follow-up interview).

Furthermore, the use of smartphones enabled the study investigators to collect data on participants' job search activities, work activity, and current mood each day. Participants received two text messages daily, each of which took only a few minutes to complete. The first was sent randomly between 9am and 6pm, and it included questions about participants' current activity and mood. The second text was sent at 7pm and the questions addressed participants' activities and mood for the whole day. To encourage smartphone respondents to complete each survey within an hour of receiving the text, participants received a $15 bonus for completing at least 75% of the interviews each week. As a result, men answered approximately 78% of all texts that they received, with two-thirds of the men reaching the 75% target completion rate. In general, smartphone respondents preferred the use of text messaging to weekly interviews and they enjoyed having access to a smartphone (Sugie, 2014).[2]

Most importantly, the smartphone interviews captured fine-grained data on changes in mood and job search activity during the early reentry period (Sugie, 2014). The variables for labor force participation, job search difficulties, and psychological distress were among the weakest variables in the current study, due to the lag in measurement periods for employment, the weak

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[1] These percentages reflect participation and completion rates for the full sample of eligible individuals. Attrition from the study was higher among smartphone participants than among interview participants (70% complete rate among smartphone users who completed the initial interview, compared to 86% for those completing interviews (Sugie, 2014).

[2] Given the high use of no-contract cell phones among former prisoners, and the importance of maintaining a stable contact number during the job search, the subsidized smartphone provided a form of reentry intervention that may improve men's likelihood of gaining employment (Sugie, 2014).

measure of labor force participation (e.g., worked at least once within a given month), and the narrow 7-day reference period for psychological distress measures. Using smartphones to capture men's current status in non-research settings would provide far more reliable measures of job search activities and mood than by use of retrospective interviews (Gaggioli et al., 2013; Sugie, 2014). For instance, men reported higher levels of anger, sadness, and stress at the first interview than were reported during smartphone interviews, and men's daily happiness levels showed substantial variability that was not captured by weekly interview responses (Sugie, 2014).

6.2.2 Testing Theoretical Concepts

Future research should examine the association between employment and crime using shorter observation periods, to assess whether the findings of this study hold with changes in lagged periods (Aaltonen et al., 2013; Horney et al., 1995; Skardhamar & Telle, 2012). Research that used monthly observation periods would be better equipped to assess whether and how employment reduces crime or crime reduces employment (van der Geest et al., 2011). Detailed information on employment status, including the number of weeks worked, average number of hours, type of job, and reasons for labor force exit, would provide insight into the associations between labor force participation, job quality, and criminal activity (Sugie, 2014; van der Geest et al., 2011).

Future research should examine the temporal association between financial need/strain, criminal activity, and criminal justice involvement. The results of this study provide cautious support for the negative effects of ongoing criminal activity on men's financial status, psychological wellbeing, and employment status. Despite this, the results provide limited support to suggest that financial strain contributes to later criminal activity. The results presented also cannot determine whether recent criminal activity was actually associated with current financial needs and psychological distress, and not vice versa, as strain theories would predict. Future research using shorter observation periods would provide stronger evidence in support of or against existing theories of work, crime, and financial need.

Future research with prisoner populations should include validated financial strain measures in surveys to be sure financial need/strain is being measured accurately. Research is also needed to assess whether financial strain is a relevant concept among young former prisoners, who may perceive limited need for goods and services commonly included in questions (e.g., inability to pay bills on time, inability to obtain medical assistance). It may be necessary to modify financial strain measures to reflect the social context faced by young and marginalized former prisoners.

6.2.3 Validating Self-Report Crime Measures

Future research should examine whether self-report measures are invariant across racial and ethnic status (Jolliffe et al., 2003; Thornberry & Krohn, 2003). The ongoing inability to adjudicate between competing explanations for disproportionate minority involvement in the criminal justice system has blunted research using self-report offending measures (Hindelang et al., 1981). Most existing studies ask respondents about delinquent and criminal activity, without also asking about criminal justice involvement. Studies should ask men to report recent criminal justice involvement as well as recent criminal involvement, so that their responses can be compared to official measures (e.g., arrests, convictions, technical violations, and institutionalizations). The correspondence between self-reported and official reports may provide insight into the reliability of self-report measures. It would also provide researchers opportunities to assess whether differential item functioning occurs by age, educational attainment, gender, and racial/ethnic status.

Studies that examine the accuracy of self-reported information would have implications for policy as well as for our theoretical understanding of delinquency and crime. In the case of this study, if it could be determined that there were no differences in the accuracy of self-reporting by racial/ethnic status, the interpretation of the findings here would change drastically. The contradictory evidence for racial and ethnic status would have major implications for policing. Namely, the duration models show that minorities had shorter times to rearrest, in comparison to Whites. However, the results of the LSEM show that Whites were significantly more likely than African Americans to have committed new crimes since release. In combination, these findings would suggest that Whites are more likely than other minority groups to commit crimes, but African Americans are still more likely to be arrested following release. This would provide unassailable support for the existence of racial bias in policing and the criminal justice system. Unfortunately, it is not clear to what extent one can draw these conclusions, absent further research on the validity of self-report measures.

6.3 Conclusion

This study has shown that previous employment program evaluations may have overstated the effects of prison-based education and employment programming. After balancing a sample of adult male prisoners on the probability of receiving employment-focused services in prison, the results of this study showed that education and employment programs had no long-term effects on labor force participation, crime, and rearrest. Null findings such as these may not appear promising, but recent employment program evaluations had concluded that such programs might have adverse consequences on participants' labor force and criminal activity (Lattimore et al., 2012). The results of this study suggest that selection effects may explain weak and negative effects of similar employment-focused programs.

The results also cast doubt on the prospect of reducing criminal activity by increasing former prisoners' labor force participation. Criminal activity had a stronger negative effect on later employment than employment had on later criminal activity. This reverses the directional effects hypothesized by many program logic models. The findings suggest the need to revise the logic models used to design and evaluate prison- and community-based employment programs for reentering former prisoners.

The study findings do not diminish the importance of employment and job training programs for men who have limited education and work experience (Bushway, 2003). Men's labor force status may not contribute to their decisions to engage in criminal activity following release from prison (Skardhamar & Savolainen, 2014), but the results do show that criminal activity severs men's connections to the formal labor market.

Finally, this study identified significant racial differences in criminal activity and criminal justice involvement after release. The findings reveal sizable differences in the likelihood of offending and being arrested among African American and White men. In the wake of Ferguson and related incidents of police brutality against young African American men, research on crime and delinquency must address the institutionalized racism that contributes to high rates of incarceration in the African American community. However, the limited ability to confirm that the measures are valid limits the extent to which we can make conclusive statements about the findings.

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Appendices

Appendix A. Employment and financial wellbeing

Source	Purpose	Sample	Methods	Results	Implications
(Apel & Sweeten, 2010b)	Effect of incarc-eration on labor outcomes, after controlling for selection bias	National Longitudinal Survey of Youth 1997; Youth 12-18 YO followed until 20-26 YO; *n* = 823 incarcerated youth	propensity score matching; fixed effects; logistic regression;	Youth experiencing first incarceration were compared to soon-to-be incarcerated youth using propensity score that models the probability of incarceration at first conviction. Compared to convicted, not incarcerated youth, incarcerated youth showed an 11% reduction in probability of post-release formal work; 5% increase in prob. of illegal earnings; 12% increase in probability of labor force nonparticipation; and a 7-week increase in the length of time spent out of the labor market. Modal work status was stable unemployment, followed by stable employment and stable nonparticipation.	Nonemployment among formerly incarcerated young men is mostly due to nonparticipation, not unemployment.
(Bellair & Kowalski, 2011)	Whether unemploy-ment and lack of jobs explain racial variations in recidivism	1,568 Ohio male parolees released in 1999; 60% African American 40% White mid-30s, mean educ. level 11th grade	Cox proportional hazards model: # of days to new incarceration for new felony	1. AA more likely than W to return on new felony when community factors excluded; racial/ethnic status no longer significant when controlling for community factors. 2. Higher % employment in manufacturing reduces hazard of new felony conviction. 3. AA living in neighborhoods with ~13%+ unemployment have much higher hazards of new felony return to prison than do W. 4. AA living in neighborhoods with ~1-7% unemployment do not have higher hazards of new felony return to prison than do W.	Neighborhood factors influence recidivism risk by influencing the probability of finding employment.

Source	Purpose	Sample	Methods	Results	Implications
(Bucklen & Zajac, 2009)	Identify determin-ants of parole success and failure	542 parole violators (PV) 186 parole successes (PS) in PA: 93% M; Violators: *M* age = 35, 28% AA, 59% W, 12% H; Successes: *M* age = 41, 34% AA, 53%W, 13% H	Mixed methods: bivariate analysis of survey data; interviews, focus groups,	1. PS and PV both stated that they were least prepared to manage finances and fin issues 2. PVs associated with antisocial peers more, PSs lived with spouse/partner more and reported better quality relationship: "family man" role 3. No real differences in FINDING job, but 70% of PSs worked the whole time under parole (~3 years) vs. 48% of PVs who did (~16 months). 4. PVs less willing to take any job and had unrealistic expectations about pay, job options. 5. Bank acct: 73% PSs, 39% PVs; PVs had more fin problems, despite lower median debt. 6. Dysphoric emotions often preceded violation. 7. Saw no benefit to violation: 91% PS, 42% PV; felt costs outweigh benefits: 95% PS, 31% PV.	1. KEEPING the job is the real problem. 2. Low basic financial management skills limit PVs coping strategies. 3. Help with soft skills and budgeting may be more important than job assistance.
(Crutch-field & Pitchford, 1997)	Test that secondary labor market workers show higher prob. of criminal activity	8,127 18+ adults in NLSY 1979	Correlation, OLS	1. Expected time at current job was related to self-reported criminal activity. 2. Time spent out of the labor force (# weeks) was related to self-reported criminal activity. 3. Significant differences between primary and secondary sector workers suggest selection into job type, not causal effect of employment.	Job quality characteristics are related to criminal involvement.
(Felson et al., 2012)	Examine whether particular types of stress are related to particular	695 male felons in Second Nebraska Inmate Study	Life event calendar (36 months preceding arrest); multi-level regress-ions: random	1. Family stress related to assaults, not others. 2. Financial stress related to property (116% higher odds), drug crimes (250% higher). 3. Unemployment associated with drug and property offenses. 4. Unstructured socializing was related to all three types of offenses.	Findings support rational choice view of crime as instrumental response to stress. Emotion reduces ability to make

Source	Purpose	Sample	Methods	Results	Implications
	types of crime		intercepts, random coefficients	5. Alcohol and drug use more related to financially motivated crimes than to assault. 6. Links between family stress & assault, and financial motivations & financial crimes, support view of crime as goal-oriented and situational behavior.	decisions and heightens perceived benefits of crime.
(Grogger, 1998)	Examine whether wages influence crime and explain racial gaps	1,134 men in NLSY79 in 1980: not in school or military (22% AA, 18% H,55% HSD)	Multivariate probit models: wages, crime, time allocation	1. Offenders earn 11% lower market wages and work approximately 6 weeks less over the year, based on total hours worked. 2. Black-White crime rate differences reflect racial wage gap and decline in youth wages. 3. Age-crime curve fits time-allocation model: As wages rise, diminishing benefits from crime.	Support crime as work: Low wages make crime more attractive; racial crime gap partially reflects racial wage gap.
(Harris et al., 2010)	Identify LFO sanction amounts and debt levels over time	500 convicted felons from Washington state (12% AA, 70% W, 9% H, 7% other; 83% male; mdn age 32 YO)	Descriptive	1. After 4 years, they still owed 77% of the amount assessed for legal financial obligations. 2. Median debt was equivalent to 36-50% of their expected annual income.	Legal financial obligations remain substantial financial burdens for many former prisoners.
(Harris et al., 2010)	Impact of LFOs on prisoners' income, wellbeing, opportun-ities, and criminal activity	50 convicted felons from Washington state (52% AA, 36% W, 12% other; 82% male; mdn age 37 YO)	Qualitative	1. Legal financial obligation (LFO) payments reduced income and increased financial stress. 2. LFOs impeded efforts to obtain education, employment, and housing. 3. Lack of regular payments incurred further criminal justice involvement. 4. Garnishments reduced their incentives to maintain legal employment and increased their incentives to commit crimes.	Legal financial obligations and other debts reduce incentives to work and provide additional sources of financial strain.

Source	Purpose	Sample	Methods	Results	Implications
(Pettit & Lyons, 2009)	Analyze the effects of incarc-eration on employment and log hourly wages	Washington DOC and UI data on 16,956 adult men (mean age 24 YO, 22% AA, 28% W, 15% H, 46% HSD)	Pooled cross-sectional time series: conditional fixed-effects logit model; fixed effects regression	1. Short-term boost in employment rates after release: 15% up for 25-29YO, 31% up for 30-34, and 38% up for 35+ YO (age at admission). 2. Employment levels decline to pre-incarceration levels within 6-10 quarters after release. 3. 5-7% decline wages for men in each age group, compared to pre-incarceration earnings.	Reentry programs that offer the prospect of stable, well-paid jobs may work with older and/or highly motivated prisoners.
(Skard-hamar & Telle, 2012)	Investigate the relationship between post-release employment and recidivism	7,476 prisoners released from Norwegian prisons in 2003 and followed monthly to 2006	Discrete-time survival models	1. Employment delayed time to recidivism, but personal characteristics accounted for employment and reduced recidivism. 2. Controlling for personal characteristics, employment remained negatively associated with recidivism. 3. Benefit receipt reduced the association between employment and lower recidivism risk. 4. Property and economic offenders were more responsive to crime-reducing effect of work than were violent and traffic offenders.	Employment is negatively associated with recidivism. Results provide support for control and strain theories.
(Visher et al., 2011)	Predict amount of time spent employed during early release period	740 men released from IL, OH, and TX prisons (74% AA, 16% W, 9% H; mean age 36 YO)	OLS	1. Prior and more intensive work experience increased the amount of time men spent working after release. 2. Having documentation and work arranged before released increased the amount of time men spent working. 3. Prison work experience was related to longer time spent working after release, unlike education or job training activities in prison.	Prior work experience identifies prisoners who will be more likely to find work upon release.

Appendix B. Programs and Interventions

Source	Purpose	Sample	Methods	Results	Implications
(Berk, Lenihan, & Rossi, 1980)	Evaluate Transitional Aid Research Project	1,951 TX and GA released prisoners in 5 study conditions	2S and 3SLS: model fit to TX data and replicated using GA data	1. Payments did not reduce prop/nonprop arrests. 2. Pay reduced work: 5-10 weeks over 12 months. 3. Parolees worked 3 more weeks than others: effect of parole on arrest through employment. 4. TARP and employment reduced arrests, but TARP reduced work (due to 25-100% tax on TARP funds for working): no overall effect	Work reduces crime by reducing unstructured socializing and by reducing financial incentives to commit crimes.
(Brewster & Sharp, 2002)	Test the effects of prison programs on recidivism	11,813 former OK DOC cases released 1991-94; mean age = 29YO;90% M; 33% AA; 68% other	Cox regression model	1. 1,044/4,752 (18.2%) of nongraduates completed GED in prison. 2. 805 (6.8% of all) completed VocEd program. 3. GED program lengthened time to return. 4. VocEd completion shortened time to return. 5. VocEd comparison group may have contained participants who did not complete the program; this may have biased treatment estimates. 6. Results likely reflect self-selection.	Prison programs can have contradictory effects on recidivism.
(Jacobs, 2012)	Evaluate the Transitional Jobs Reentry Demon-stration	1,813 men (912 TJs, 901 JS); mean age = 35 YO, 82%AA, 10% W, 4% H		1. Transitional Jobs condition shows short-term boost in employment: 95% of TJ ever worked over 2 years vs. 65% of Job Search condition. 2. Increase faded by Quarter 5: no difference in unsubsidized employment/earnings in year 2. 3. No differences in various measures of recidivism across sites. 4. Financial incentives may boost participants' labor force participation.	Transitional jobs programs do not appear to increase unsubsidized employment levels or reduce recidivism.

Source	Purpose	Sample	Methods	Results	Implications
(Redcross et al., 2012)	Evaluate the Center for Employ-ment Opportun-ities	977 parolees using the Center for Employment Opportunities (568 T, 409 C); 93% male, 64% AA, 31% H, mdn age 34 YO	Random assignment to program and control group; OLS	1. Subsidized jobs did not lead to unsubsidized employment: Treatment members showed higher employment levels than did control members during the program, but employment rates decline to control group after first year. 2. Recidivism reductions persisted over 3 years, even though employment levels declined after the first year. 3. Treatment members who enrolled in the program within 3 months of released showed 16-22% reductions in recidivism.	Program modifications should address factors that keep participants from transitioning to unsubsidized employment.
(Saylor & Gaes, 1997)	Evaluate Post-release Employ-ment Project	Inmates in PREP: 57% only prison industry work; 19% work and VocEd; 24% VocEd/ app-renticeship	comparison group identified using propensity scores; Cox proportional hazards	1. 14% higher probability for program group to be working 12 months after release. 2. 35% lower recidivism rate for program group after 12 months, relative to comp group. 3. Program effects over 8-12 years: 24% recidivism reduction for prison industry group and 33% reduction for VocEd/app group.	Controlling for selection effects, prison work and training programs help reduce recidivism.
(Sedgley et al., 2010)	Impact of education and two types of prison work programs on recidivism	4,515 male prisoners released from Ohio prisons in 1992 and followed to 2002	Propensity score matching, Weibull mixture model	1. True nonparticipants appeared different from participants in one/more program types. 2. Each activity delayed time to return to prison. 3. Interaction terms showed diminishing returns to participation in more than one activity, but education programs appeared to complement skills obtained from work programs. 4. Program coefficients remained significant when propensity scores were added to the model, and the prison industry propensity score coefficient was not significant.	Each program appeared to reduce prison costs. Evaluating programs separately can mask benefits due to contamination effects among nonparticipants.

Source	Purpose	Sample	Methods	Results	Implications
(Steurer et al., 2001)	Impact of prison education on post-release employment and recidivism	3,170 inmates from MD, MN, and OH in the OCE/CEA Recidivism Study (1,373 educ, 1,797 comparison)	Bivariate and multivariate regression	1. Education participants exhibited lower recidivism rates than the comparison group. 2. Participants earned slightly higher wages each year, although employment rate was slightly higher for nonparticipants. 3. Education participants were motivated less by labor outcomes than to please prison staff and parole boards.	Education program participation appears to improve reentry outcomes.
(Tyler & Kling, 2007)	Examine whether GED attain-ment improves labor market outcomes among former prisoners	12,956 former FL prisoners (1,967 GED holders, 1,400 GED attempters, 9,589 dropouts)	Panel data analysis of administrative earnings data using fixed effects estimation: 12 quarters earnings data	1. Non-White men who earned GEDs earned $200 more per quarter than demographically similar nonparticipants. Non-White men who participated in GED programs without earning GEDs exhibited nearly the same increase in quarterly earnings. 2. Earnings advantages among Non-White GED holders persisted for 2 years after release. 3. White men accrued no labor market benefits from GEDs.	GED programs may improve labor outcomes among the most severely disadvantaged in the labor market.
(J. A. Wilson & Davis, 2006)	Evaluate the Project Greenlight Reentry Program	735 New York state parolees (344 GL, 278 TSP, 113 Upstate); 55% AA, 37% H, 6%W, mdn age 33 YO	Cox proportional hazards model of time to arrest/time to felony arrest	1. Project Greenlight did not substantially improve participants' employment or housing. 2. Higher proportion of GL participants were arrested during the first year (33% of GL, 27% of Upstate, and 24% of TSP group). 3. GL participants showed significantly shorter time in weeks to first arrest, first felony arrest, and to parole revocation.	Poor implementation can worsen reentry outcomes.

Source	Purpose	Sample	Methods	Results	Implications
(D. B. Wilson et al., 2000)	Meta-analysis of corrections programs: education, vocation, and work	33 studies of corrections programs that measured recidivism and used a nonparticipant comparison group	Meta-analysis	1. Postsecondary education programs showed largest reduction in recidivism (37% rate compared to 50% assumed rate). 2. Recidivism reductions: vocational training (39%); Correctional work/industries (40%); Basic Educ/GED (41%); other (43%). 3. Heterogeneity across programs indicates that within categories, some programs are more effective than others are.	Weak methodology means that recidivism reductions could reflect participant characteristics, not program effects.
(Zweig et al., 2011)	Identify recidivism effects of the CEO program for low-, med-, and high-risk former prisoners	977 parolees using the Center for Employment Opportunities (568 T, 409 C); 93% male, 64% AA, 31% H, mdn age 34 YO	Create risk of recidivism score for each person and create 3 subgroups; logistic and OLS regression	1. Gender, age, and prior arrests predicted recidivism risk: low = under 25^{th} percentile, med = 25^{th}-75^{th} percentile, and high-risk = above 75^{th} percentile. 2. CEO participation reduced high-risk former prisoners probability of rearrest, reconviction, and number of arrests in year 2; the program did not affect recidivism outcomes among high-risk members in year 1, when participants held subsidized employment	High-risk former prisoners were most responsive to the treatment: subsidized employment and case management for 12 months.

Appendix C. Group-Based Trajectory Model

This study models prior offending trajectories using annual arrest indicators for the years preceding their SVORI prison term (Haviland & Nagin, 2005; Lattimore & Steffey, 2009; Nagin, 2005). The SVORI adult male sample is assumed to comprise a mixture of *J* underlying trajectory groups. The composition of groups can be described by $P(Y_i) = \sum_j \pi_j P^j(Y_i)$, in which Y_i is a longitudinal sequence of annual arrest counts from age at first arrest to the SVORI term, $P(Y_i) =$ the probability of Y_i, $\pi_j =$ the probability of group *j*, and $P^j(Y_i) =$ the probability of Y_i given membership in group *j*. Conditional on group membership, subject *i*'s observations at times $t = 1, 2, 3, \ldots, T$ are random independent variables. Probabilities of membership in each group are modeled using a multinomial logit function $\pi_j = e^{\theta j} / \sum_1^J e^{\theta j}$, where θ_1 is set to 0 to ensure that π_j is estimated such that men's probability of membership in each trajectory group falls between 0 and 1 (Jones & Nagin, 2007).

Men's arrest indicators are assumed to follow the logistic distribution. The group-based trajectory model (GTM) is depicted by the equation

$$\ln(\lambda_{it}^j) = \beta_0^j + \beta_1^j Age_{it} + \beta_2^j Age_{it}^2 + \beta_3^j Age_{it}^3 + \beta_4 Viol_{it} + \beta_5 Prop_{it} + \beta_6 Drug_{it} + \beta_7 Pub_{it},$$

in which λ_{it}^j= the expected number of arrests of subject *i* at time *t* in each year leading up the SVORI status incarceration, given membership in group *j*, Age_{it} = subject *i*'s age at time t, Age_{it}^2 and Age_{it}^3 = squared and cubed forms of Age_{it}, and $Viol_{it}, Prop_{it}, Drug_{it},$ and Pub_{it} are each indicators of arrest type for arrests at time *t*. The model allows the vector of parameters (β^j) to vary freely across groups (Jones & Nagin, 2007).

The number of trajectories identified by the model can depend upon the length of the observation period used to generate trajectories and the number of subjects in the sample (Nagin & Tremblay, 2005). The GTM may identify groups even when all individuals in the sample are homogenous with respect to criminal background and offending propensity (Brame et al., 2012; Nagin, 2005; Nagin & Tremblay, 2005). By design, the model will fit the number of groups specified, and it is the researcher's responsibility to determine the appropriate number of groups by comparing the fit of models identifying different numbers of groups (Brame et al., 2012). The Bayesian (Schwarz) information criterion (BIC) is used to compare non-nested trajectory group models, $BIC = -2\ln L + K \ln n$. The formula penalizes overfit models by increasing their BIC value, so low BIC values identify models that provide better fit to the data than other models. The most parsimonious model with an optimal BIC value is generally selected as the best model (Brame et al., 2012; Nagin, 2005; Nagin & Tremblay, 2005).

Bayes theorem is used to generate for each individual a nonzero probability of membership in each identified group j.

$$Prob(group = j|observation\ i) = \frac{f(observation\ i|class = j)Prob(class\ j)}{\sum_{j=1}^{J}(observation\ i|class = j)\ Prob(class\ j)} = w_{ij}$$

These posterior predicted probabilities of group membership will be included in the propensity score models as continuous measures (Jones & Nagin, 2007). For duration models, individuals will be assigned to the group for which they have the highest posterior predicted probability of membership. Predicted group membership will be used to examine whether missing data are ignorable, for purposes of the longitudinal structural equation model sample using follow-up data (Allison, 2012; Nagin, 2005; Piquero, Farrington, Nagin, & Moffitt, 2010).