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CLASSIFYING DRUG MARKETS BY TRAVEL PATTERNS: TESTING REUTER AND MACCOUN'S TYPOLOGY OF MARKET VIOLENCE

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ABSTRACT

CLASSIFYING DRUG MARKETS BY TRAVEL PATTERNS: TESTING REUTER AND MACCOUN'S TYPOLOGY OF MARKET VIOLENCE

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Doctor of Philosophy
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Research to date has demonstrated significant relationships between the presence of outdoor drug markets and violent crime. Scholars have neglected however, to consider the role of travel distance on the drugs/violence nexus. The current study examines whether features of the distributions of travel distance to markets of drug buyers, drug sellers, or the interaction between the two distributions predicts drug market violence levels net of surrounding community demographic structure. Reuter and MacCoun's (1992) as yet untested model about the connections between drugs and violent crime, predicts that the interaction of drug seller and buyer distance distributions from varying distances more powerfully drug market violence levels than buyer and average distance averages. This suggests that how the travel patterns of the two major participants in drug markets intersect is key to understanding differences. That model is tested here. In addition, for comparison purposes, impacts of buyer and seller travel median distances are modeled separately.

This work uses 5 years (2006-2010) of incident and arrest data from the Philadelphia Police Department.

Reuter and MacCoun's model will be tested using the following analytical techniques. First, a methodology for locating and bounding drug markets using a nearest

neighbor, hierarchical clustering technique is introduced. Using this methodology 34 drug markets are identified. Second, hierarchical linear models examining buyers and sellers separately predict travel distances to drug markets. Arrestees are nested within markets. This technique separates influences on distance arising from arrestees from drug market distance differences. Third, how market level median travel distance affects within drug market violence is considered. Specifically, the main effects of median buyer travel distance and median seller travel distance on drug market violence are captured using separate Poisson hierarchical linear models. Finally, impacts of the interaction between buyer and seller distance, Reuter and MacCoun's (1992) focus, are explored in another series of generalized hierarchical linear models.

The main findings from the dissertation are as follows: 1. Results provide partial support for Reuter and MacCoun's drug market-violence model using multiple operationalizations. Public markets—those in which buyers and sellers travel from outside their own neighborhoods—are expected to be the most violent. 2. Separate raw distance measures for buyers and sellers correlate with within-drug market violence, after controlling for community demographics. 3. A negative effect of socioeconomic status and violence holds even when modeled with drug market variables. 4. As the proportion of crack cocaine sales within drug markets increases so too does within-market violence.

Conceptual implications highlight the need to investigate social ties as an intervening variable in the travel distance → drug market violence relationship. It is not clear from this research whether the travel distances of drug offenders in some way explains the amount or strength of social ties in a drug market, which in turn serves to suppress or elevate within-drug market violence.

Policy implications suggest that Reuter and MacCoun's drug market types may connect with specific policing responses. Policing efforts may not receive much support from community residents because dense social networks may discourage reporting illicit activity. Markets drawing dealers and customers from farther away, and located around commercial and recreational centers may be amenable to place-based policing initiatives and coordinated intervention strategies with multiple city agencies.

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CHAPTER 1:

FOCUS

The systemic nature under which drug dealing and buying takes place appears to be largely responsible for violence within and near drug markets (Goldstein, 1985). The illegality involved in drug markets places buyers and sellers in complicated situations (Eck, 1995). Because both sellers and buyers are breaking the law and neither desires arrest, they must make a personal connection. That is, they must convince one another they are not police officers. Further drug buyers seek reassurances dealers will not rip them off. Additionally, dealers seek reassurances buyers will not try to steal their money. With all of these constraints in place, these actors must converge in time and space in such a way that sellers can profit and buyers satisfy narcotic dependencies. Although police enforcement of street drug markets can promote an indoor drug market economy (Rengert, Ratcliffe, & Chakravorty, 2005), conducting activity on the street still provides for some buyer security (St. Jean, 2007) and sufficient dealer access to potential buyers (Eck, 1994, 1995). Illegal street drug markets therefore provide opportunities for all of these needs to be addressed.

Drug buyers or sellers in illegal street markets cannot seek assistance from the criminal justice system to address market grievances. Those might include watered-down drugs, robbery, and the encroachment of rival sellers on established territory. This isolation from legal remedy may explain why involved individuals seek self-help or retaliation through violence (Black, 1976).

The deleterious effects of illicit drug markets in urban communities have been thoroughly demonstrated by past scholarship. Outdoor drug markets in disadvantaged areas are dangerous locations (Curtis & Wendel, 2007). The issue is not just increased drug use by nearby residents (Saxe et al., 2001). More importantly is the potential violence associated with outdoor drug markets (Rengert, 1996b). Violent gangs are involved with the drug trade (Venkatesh, 2008). For example, recent research found drug corners are associated with substantially higher violent and property crime levels, especially when multiple gangs were associated with a corner (Taniguchi, Ratcliffe, & Taylor, 2011).

Although it is clear that there is a covarying relationship between drug crime and violent crime (Gorman, Zhu, & Horel, 2005), the nature of that relationship stands to be clarified through theory testing. In response, this dissertation questions whether the variation in drug market violence can be explained by Reuter and MacCoun's (1992) hypothesis that the interaction of drug market participants' travel-to-crime distance distributions shape drug market violence levels. In other words, this dissertation examines the extent to which stable and temporally varying patterns of buyer and seller journeys to markets covary with violent crime counts. To this author's knowledge it is the first empirical test of their hypothesis, using 5 years (2006-2010) of incident and arrest data from the Philadelphia Police Department.

This research investigates determinants of buyer and seller travel distances after operationalizing drug markets. Two approaches are used to examine the relationship between travel distance and market violence. The first separately models aggregate buyer or seller travel distance on within-market violence, controlling for market and community characteristics. The second models the interaction of buyers and sellers from varying distances on within-market violence. The methodology of this research is described below.

First, this research addresses the above inquiry by proposing a method to spatially delineate drug markets using a nearest neighbor hierarchical clustering technique. Prior research has failed to agree on how to operationalize drug markets—a problem derived from of the lack of agreement on conceptualization. Definitions of drug markets not only vary by academic discipline (Ritter, 2006), but by studies within a discipline (Hunt, Sumner, Scholten, & Frabutt, 2008; Rengert, Chakravorty, Henderson, & Bole, 2000). At the most basic level, markets are merely places and standards by which exchanges of goods take place (Reuter, 2000); however, confusion takes place when one considers the multiple ways by which drug markets can be operationalized.

Second, using the spatial locations of drug markets, distance buyers and sellers travel to such areas is determined while controlling for individual and market level correlates using hierarchical linear modeling (HLM). The purpose of this component of the investigation is to understand the role of individual and market demographics as well as drug choice on the distance-to-crime decision. The advantage of HLM is that it can separate individual (drug buyer or seller arrestee) from ecological (market) effects (Raudenbush & Byrk, 2002).

Third, this research examines the extent to which buyer travel distance and seller travel distance distributions account for violence levels within drug markets. An understanding of travel distance may inform interdiction strategies. For example, street closures and traffic routing measures to reduce drug market stability would be of little use if a disproportionate number of a market's patrons are residents of the surrounding neighborhood who walk to the offense location; however, such policies may be worthy of consideration for markets where offenders are traveling by vehicle to unfamiliar territory.

Fourth, and most important, the distance interaction among buyers and sellers traveling to markets is used to evaluate Reuter and MacCoun's (1992) classification of drug markets and their hypothesized evidence links. In essence, their model implies that the market violence depends, in part, on social ties. Formation of social ties among buyers, sellers, and community residents depend, in part, on buyer and seller travel distance. Venkatesh (2008) found that gang organizations frequently sponsor community events and provide public housing security in exchange for resident tolerance. Even in middle class communities, research has found that close social networks allow gang members and residents to be connected through legitimate and illegitimate social networks; these, in turn reduce the ability of communities to regulate illicit activity (Pattillo, 1998). Other work has found that collective efficacy may have unanticipated effects on preventing and addressing drug sales (St. Jean, 2007). Neighbors who are familiar with sellers are less likely to report their behavior to the police and appear to be more likely to work with other community members to defend the actions of drug sellers (Fagan, 1992). These works of identifying an affinity between local sellers and residents would suggest that there is an investment of local drug sellers in the community. Reuter and MacCoun's model, although it aligns with this earlier work, goes further. It classifies drug markets into types, based on the distribution of travel distances to markets of <u>both</u> buyers and sellers. It further suggests market type links to violence levels in the market.

The current work presents the first known operationalization of their typology and test of their violence prediction.

The setting is Philadelphia, Pennsylvania—an urban area well documented for its decayed social conditions (Anderson, 1999). The city comprises just over 130 square miles and 1.5 million residents. Demographically, the city contains both substantial African American (42%) and white (43%) populations. About one fifth of its residents live in poverty (U.S. Census Bureau, 2000). Philadelphia was rated as one of the most dangerous cities in America in 2009, holding the 21st position out of 393 cities (Morgan, Morgan, & Boba, 2009). In 1995 Philadelphia was designated as part of the Philadelphia/Camden High Intensity Drug Trafficking Area, a recognition that the area retains "a well-developed transportation infrastructure… that is ideally suited for the movement of illicit drugs and drug proceeds to and from the region" (NDIC, 2009, p. 3). As such, there is much to gain from studying the relationship among drug markets, violence, and travel distance. Results for the work have the potential to help target police resources and drug intervention services.

In sum, there are five objectives of this dissertation. The first is to spatially describe Philadelphia drug markets during the 5 year (2006-2010) study period. Second, following the delineation of illicit markets, it describes and predicts buyer and seller journeys to drug markets. Third, it separately tests whether buyer and seller typical travel patterns provide additional explanatory power for predicting drug market violence levels after controlling for socioeconomic status, residential stability, and race. Fourth, it tests whether Reuter and MacCoun's drug market types based on distance configuration significantly predict violence levels after controlling for surrounding demographic structure.

CHAPTER 2:

LITERATURE REVIEW

Introduction

The purpose of this work is to clarify an empirically-proven relationship between drug markets and violent crime. While research has demonstrated that the illegal nature of drug markets predisposes dealers and sellers to violent situations (Jacobs & Wright, 2007), what has yet to be explored is whether the distances traveled by market participants are predictive of violent crime within drug markets. This inquiry is significant, in that it provides the opportunity to possibly understand why some drug markets are more violent than others, suggest *who* is responsible for local drug crime (local residents or outsiders), and provide suggestions for interdiction.

The nature of the above inquiry requires several smaller questions to be investigated. In other words, in order to study the impact of the travel distances of drug dealers and buyers on community violence, one must first ask: What is a drug market? How one chooses to conceptualize drug markets will certainly suggest how it should be operationalized. Second, how far are buyers traveling to their arrest locations and does such data account for the variation in violence levels across drug markets? A similar question is posed for drug sellers. Third, does the travel distance of drug buyers and sellers have implications for market violence? These questions are collectively used to build on the fourth and most important research inquiry: Is there empirical support to qualify the hypothesis that drug market violence depends (at least in part) on the varying distances by which *interacting* buyers and sellers travel?

This review, therefore, is structured to describe knowledge relative to the aforementioned questions. The first section summarizes knowledge on the drugs and violence nexus and focuses on the systemic nature by which violence takes place, which is a salient feature of this research. The second section seeks to understand how prior research has defined the concept of drug markets. The third investigates research on the journey to crime. The fourth section reviews Reuter and MacCoun's (1992) hypothesis of violence within drug markets and considers possible theoretical and empirical support.

Violence in and around drug markets

Perhaps the most detrimental aspect of urban drug markets is the violence by which they are often characterized. Concentrated disadvantage appears to be strongly related to drug market activity, with drug market activity in turn having a strong causal connection with robbery rates (Berg & Rengifo, 2009; Bursik & Grasmick, 1993). Such communities tend to be socially disorganized and unable to regulate drug crime and the related violence that it engenders (Berg & Rengifo, 2009). However, even controlling for sociodemographic factors such as instability, heterogeneity, and deprivation, drug activity still has a significant positive effect on assault and robbery rates (Martínez, Rosenfeld, & Mares, 2008). Other research has explored the possibility that the drugs/violence nexus is contingent upon sociodemographics. Ousey and Lee (2002) found that increases in drug arrest rates were positively related to homicide rates; however, that relationship is contingent on the preexisting level of resource deprivation.[1] In other words, when the level of resource deprivation is at or above the average, drug crime rates are positively

[1] "Resource deprivation is a multi-item (poverty rate, unemployment rate, percentage black, percentage of female-headed households with children, mean household income, the Gini coefficient of family inequality, and the percentage persons aged 25 and over who have not completed high school) index that taps the degree of structural disadvantage in a city" (Ousey & Lee, 2002, pp. 83-84).

related to homicide rates, but when the level of preexisting deprivation is less than the average the relationship is negative.

Furthermore, outdoor drug markets tend to be associated with the use of guns, and as a result, violence has the potential to be fatal within this context (Messner et al., 2007; Mieczkowski, 1992). Research has shown that homicide levels of the mid 1980s and early 1990s are largely attributable to the proliferation of guns as young minority males sought protection while engaging in the risks of drug dealing (Blumstein, 1995). Not only are guns instrumental in protecting inner city dealers from the risks of the drug trade, carrying guns and being prepared to use them as necessary is a symbol of status; and, ideally such presentations of self serve to protect dealers from their rivals (Anderson, 1999).

Youth involved in the drug trade have significantly more arrests, more commitments to detention facilities, are younger at first arrest, and are more likely to be re-arrested within 6 months of release than their non-dealing counterparts (Duncan, Kennedy, & Smith, 2000). Additionally, young drug dealers are more likely to exhibit violent conduct disorder behaviors such as using weapons in a fight and being physically crueler than non-dealers (Duncan, et al., 2000). Research on the initiation of juveniles in drug dealing has also found self-reported increases in antisocial behavior post-initiation, especially in violent crimes such as rape, strong-arming, and assault with weapons (van Kammen & Loeber, 1994). Nonetheless, although youth involvement in gangs is expected to facilitate criminal behavior (Hirschi, 1969), violence is a common part of youth gang activity and drug dealing does *not* increase the frequency of gang violence (Fagan, 1989). Related research by Bjerregaard (2010) found drug dealing by gang members to be unrelated to assaults. However, they are more likely to carry guns, lending support to prior research by Blumstein (1995) and Anderson (1999). Other research has found that gang members that sell drugs are almost twice as violent as non-gang drug sellers and non-selling gang members (Bellair & McNulty, 2009).

Research has also found the above relationships among drugs and violent crime to demonstrate spatial dependency (Zhu, Gorman, & Horel, 2006). Using data from Houston, Texas, Gorman and colleagues (2005) found that drug crime accounted for 72% of the variation in violent crime, with significant spatial lag effects. Identifying communities that demonstrate high levels of violent crime *and* drug activity has been shown to be valuable in focusing police strategies (Hunt, et al., 2008). Spatial research has also revealed that not all drug markets are violent, suggesting that research should consider the systemic factors by which they vary (Lum, 2008). Such considerations are explored below.

Theoretically speaking, Goldstein's (1985, 1998) tripartite conceptual framework describes models by which drug markets engender violence. The psychopharmacological model posits that the ingestion of certain narcotics may lead to erratic, violent behavior. Such violent behavior may be the result of not only the ingestion of drugs, but withdrawal symptoms associated with "coming down" or "crashing." It is important to note that not only can the ingestion of drugs lead to violent perpetration on behalf of the user, but also victimization. Drugs that alter the mental state of a user may lower their vigilance and decision-making skill, in turn making them viable targets for violent victimization. Furthermore, some people make the decision to engage in crime but lack courage to do so. Drugs may be used to lower the anxiety of a potential offender prior to engaging in the violent act.

According to the economic compulsive model, users engage in economically motivated crimes to obtain money or collateral useful to exchange for drugs. Crimes of this nature include shoplifting, purse-snatching, and more violent offenses such as robbery. Users may not have the intent, per se, to engage in violence during these events yet the milieu of unknowns sometimes elevates tension among the user, victim, and bystanders. For example, victims may react violently to the transgression, bystanders may act on behalf of victims in a violent manner, or unbeknownst to the user the target may have a weapon. In turn, the user must react to these situations as they arise, with the potential to also react violently (Goldstein, 1985).

The systemic model of violence argues that the violent nature of drug markets is normative to the nature by which illicit drug transactions take place. In other words, because illicit drug markets operate in a world unregulated by legal standards, disputants within drug markets are unable to seek the help of the criminal justice system to settle conflicts. As a result, market participants use alternative measures to redress their grievances, and at times the measure of choice is violence (Goldstein, 1985).

The systemic model is rooted in Donald Black's (1976) theory of law and self-help (Jacques, 2010; Jacques & Wright, 2008; Ousey & Lee, 2004). According to Black, social groups may employ a number of methods to address conflict; however, the decision to resort to violence depends on a social group's relative position on the social ladder. "In other words, as people or groups gain status, their access to law increases and, in turn their involvement in retaliation decreases" (Jacques, 2010, p. 188). Because of this, marginalized groups may be more likely than more highly-positioned, wealthier groups to resort to violence, or what Black describes as "self-help", to settle disputes.

In turn, lower status or less "respectable" groups such as drug offenders are subject to additional social control by the law, even though they cannot use the law to their benefit. The perceived threat by higher status members of drug dealers and buyers may allow higher status members to use their social positions to apply strict penalties to drug offending. This would further increase the isolation of drug offenders from legal remedies leading their problem-solving solutions to be centered around violence (Black, 1976).

It is important to note that the tripartite conceptual framework is not a theory, but a typology of drug-related violence. The proposed models are not mutually exclusive as it is possible for drug-related violent events to be characterized by more than one model. For example, a drug dealer may choose to ingest drugs to reduce their anxiety (psychopharmacological) before robbing a rival drug dealer for encroaching on their territory (systemic). Similarly, addicted drug users suffering from withdrawal symptoms may engage in robbery to satisfy their dependency (psychopharmacological and economic-compulsive). The majority of research reviewed below focuses on systemic-related drug violence. It is believed that the systemic model is more readily applicable to the ecological nature of this study which examines variation in violence among drug markets due to travel distance; rather than drug-induced motivations to engage in violence (psychopharmacological) or violence that results from the need to acquire resources to obtain drugs (economic-compulsive). Goldstein (1985) lists a number of ways in which systemic violence manifests itself. They are described below.

Drug dealer disputes over territory

One of the unique aspects of gang behavior is that it is extremely territorial in nature (Thrasher, 1927; Venkatesh, 2008). Gangs typically have a set space where they carry out leisure, and "business-related" activity which essentially serves as a node or base within their routine activities (Tita, Cohen, & Engberg, 2005). Drug selling and shots fired calls to the police appear to concentrate within and near such areas, which may be suggestive of conflict between rival gangs or at least between the gang in question and the community (Tita & Ridgeway, 2007).

Taniguchi, Ratcliffe, and Taylor (2011) examined the impact of gang set space on violence using data from the Camden County (NJ) Prosecutor's Office that provided street corners where known gang members were witnessed selling drugs. Results indicated that corners that were a part of gang territory were associated with about two times higher counts of violent crime events than corners that were not a part of gang set space. Furthermore, corners where multiple gangs have sold or those under dispute experienced violent crime counts almost 3 times higher than non-gang corners. These results lend support to Goldstein's (1985) systemic model of violence, suggesting that drug gangs resort to violence to address problems with territory encroachment by rivals (Decker & van Winkle, 1994).

Assaults and homicides committed within dealing hierarchies as a means of enforcing normative codes

Other work has attempted to apply the structure and behavior of legitimate businesses to drug markets (May & Hough, 2001, 2004; Murji, 2007; Rengert, 1996b).

For example, Curtis and Wendel (2000) classified markets by their organizational and leadership styles. Freelance distributors are markets that lack any sort of conceptual organization. These markets are characterized by individuals who sell for themselves without attachment to a higher authority. Although they afford sellers autonomy they also leave them without protection, and as a result freelance sellers are frequent victims and offenders associated with violent acts (Curtis & Wendel, 2000, 2007; May & Hough, 2004).

Socially-bonded markets involve a sense of hierarchy and organization, albeit not very sophisticated, and are "… usually based upon extra-economic social ties—typically kinship, race, ethnicity, nationality, and/or neighborhood" (Curtis & Wendel, 2000, p. 133). They may also use the organization to support the needs of the social group through the provision of employment (through drug selling).

Corporate-style distributors are the most organized category (Curtis & Wendel, 2000). In these markets there are clear distinctions between upper-level management and lower-level street dealers. Because trust and loyalty are critical to maintaining the organization and avoiding police detection, lower-level workers are intimidated via violence to dissuade behaviors such as talking to the police or hiding profits (Farr, 2010; Venkatesh, 2008).

An alternative form of drug distribution is the order-delivery method (Curtis & Wendel, 2007). The availability of cell phones and pagers in the 1990s revolutionized the ways that drug transactions take place, allowing dealers to shift from fixed-site dealing to decentralized operations. As implied, buyers can call a frequently changing cell phone number, place an order, and set up an exchange location. Ethnographic research of a New York-based drug delivery business reveals that it operated similar to a legitimate business. Three co-owners were responsible for managing the business, which employed between 10 and 15 'delivery-men', and two or three 'dispatchers' responsible for taking orders and directing delivery-men to exchange locations. Curtis and Wendel (2007) argue that order-delivery distributors are less attached to place and, as a result, do not have to compete with rival sellers for outdoor sales locations. Participants in the order-delivery business, therefore, engage in less violence than freelance distributors who are left to their own devices to service and defend a profitable drug corner.

Research shows that buyers prefer the safety of the order-delivery method over buying drugs from a street dealer (Mieczkowski, 1992). Buyers feel more secure from transactions that take place using the delivery method because they usually occur within a social network. Nonetheless, even transactions that take place within social networks have the potential to go wrong. Below, Brownstein et al. (1995) describe a conflict between two users and a drug delivery-woman:

> The older woman and the man began to argue. He hit her. The respondent [delivery-woman] intervened, asking to get her money so she could leave. Then she claims she fell and was knocked unconscious. When she awoke, the older woman was dead on the floor, and the man was standing over her, mumbling. He saw the respondent, and she claims he threw her out the window. She fell six stories and broke her ankle and hip (p. 492).

Robbery violence related to the social ecology of copping areas

Goldstein (1985) argues that the nature of drug market areas is such that they provide a substantial number of robbery targets. Furthermore, as stated earlier, the illegality of the transactions taking place prevents robbery victims from seeking the help of police and the courts. This renders drug offender robbery an event largely hidden from detection of the criminal justice system.

Fixed-site drug distribution and use locations such as crack houses and shooting galleries present opportunities for robbery victimization (Brownstein, et al., 1995). The following quote from a drug robber respondent interviewed by Brownstein and colleagues illustrate this point:

> I had noticed one of the guys that had been standing behind the scale went for his pocket, and I was always told, "Never allow anybody to move after the specific orders were given." So when he went to go, I pistol-whipped him. When I pistol-whipped him, the bullet hit the next guy. … Actually, the one I took his life, it wasn't called for. The bullet wasn't meant for him. The bullet wasn't meant for either of them. It was to show [that] when orders are given, don't do nothing but what you are supposed to do (1995, p. 490).

Robberies of drug dealers and the usually violent retaliation by the dealer or his/her bosses

Jacobs and Wright (2007) conducted semi-structured interviews of 29 drug dealer robbers from St. Louis, MO to understand the economic and moralistic motives behind robbery. Market-related violations occur when systemic issues such as disagreements between partners or rivals lead to conflict which may take place in the form of robbery. The victim is likely to seek revenge but may not be able to find the transgressor, so they may rob another drug dealer to recover their economic loss. However, in the event that the victim can locate their robber they may seek revenge to send a moral message that they are not to be messed with. Below, a dealer describes what happened when she encountered the woman that robbed her of $350 and a large stash of marijuana:

> My partner had a big stick. She was hitting her like in her ribs. … I was just hitting her in her face … stomping her ass … whipping her ass … big old cut … right back here by her ear … face all fucked up … and then I

> got like directly in front of her and I kind of like stomped her down in a sack … "You taking my motherfucking shit. You ain't gonna do that shit no more. I ain't the bitch to play with." … [We took a] thousand dollars … two quarter pounds [of marijuana] … big [diamond rings] …nice little chain … earrings … We took everything (Jacobs & Wright, 2007, pp. 6-7).

Punishment for selling adulterated or phony drugs

At times dealers publicly humiliate drug addicts, refuse to sell them drugs, sell watered-down drugs (Brownstein, et al., 1995) or offer to sell them drugs at unreasonable prices—all things of which addicts find morally offensive (Jacobs, 1998). Drug addicts may act out their frustration by robbing drug dealers of money, drugs, or both to send a moral message and/or to satisfy their narcotic dependency (Jacobs & Wright, 2007). Dealers recognize the danger of selling watered-down drugs, as buyers that may be experiencing withdrawal symptoms are known to engage in violence against dealers when they discover that their drugs are of poor quality (Jacobs, 1998). Dealers tend to dissuade conflict and violence by blaming buyers for having such a high tolerance, warning buyers beforehand that their product is of poor quality, or blaming the drug quality on the distributor (Jacobs, 1998).

In summary, research has provided some support for Goldstein's (1985) systemic model of drug market violence. The presence of drug-selling gangs is related to higher counts of violent crime and substantially higher counts when rival gangs occupy a similar area (Taniguchi, et al., 2011). Additionally, there is evidence that the more organized a drug selling organization is, the more likely it is to engage in violent behavior (Curtis & Wendel, 2000; May & Hough, 2004). Aside from the implications of organizational behavior on the drugs/violence nexus, conflicts among rival dealers and buyers create conditions favorable for robbery victimization and offending (Jacobs & Wright, 2007).

Violence between the community and drug dealers and participants

A significant aspect of drug market violence overlooked by Goldstein (1985) is that which may take place between the community and buyers and/or dealers. Law abiding residents living in drug market areas may become violent against users and dealers if they feel the criminal justice system is ineffective in addressing the problem (Rengert, 1996b). Such vigilante justice, however, places law abiding residents at risk of bodily harm, as well as sanctioning by the criminal justice system (Brownstein, et al., 1995). To a lesser extent, residents may also become verbally hostile to condemn drug dealing in their communities, but even this has the potential to lead to violent confrontations if a dealer sees the area as profitable (St. Jean, 2007).

Operationally defining a drug market

Understanding the conditions under which drug market systemic violence takes place is extremely limited without being able to articulate what a drug market is. If research is not able to define drug markets then it certainly cannot determine whether violence is taking place within them spatially, and within the context of them. However, the problem is not that scholars cannot define such a term, but that they have done so in many different ways.

Research has failed to agree on how to conceptualize drug markets. In the most general sense, markets are merely ways in which buyers and sellers relate to one another possibly through the sale/purchase of antiques, foods, or illicit drugs; markets also imply places where exchanges occur such as antique shops, grocery stores, or street corners (Reuter, 2000). Murji (2007) argues that “at the most banal level, all drug transactions are market relations in that they entail an exchange between sellers, buyers, traders, and so on" (p. 782). Reuter (2000) proposed a similar idea, defining a drug market as "... a place to which a drug user can go with fair confidence of finding a willing seller, perhaps even one whom he does not know" (p. 7).

However, research indicates that the conceptualization of drug markets is highly dependent upon the disciplinary lens used (Ritter, 2006). Economic studies define markets as exchanges for commodities based upon principles of supply and demand. Criminological research focuses on the illegality of drug exchanges, behavioral and sociological theories explaining those exchanges, and the responses of law enforcement. Ethnographic work, however, describes the experiences of those involved in and/or exposed to illicit drug exchanges within the broader social context. Admittedly, related yet distinguishable definitions bring confusion to drug market research because "the absence of a unifying definition is important—one cannot presume to know what a particular discipline or researcher is referring to when the term 'drug market' is used" (Ritter, 2006, p. 460).

Understanding how researchers conceptualize drug markets is important because it has clear implications as to how drug markets are operationalized as a variable and for interpreting results. Perhaps the primary reason that research has operationalized drug markets in so many different ways is because—as illustrated above—not only does the disciplinary paradigm influence one's perception of drug markets, but within disciplines the drug market concept is continually modified to address innovative research inquiries. Below is a summary of how literature has produced variation in drug market conceptualization and operationalization.

Within criminology, drug markets have been conceptualized in a number of ways. Eck (1995) alludes to the systemic nature of drug markets in stating that they are adaptations to the unique situations buyers and sellers encounter while making transactions such as; avoiding police attention, the inability of relying on the police to settle disputes, and the need to conduct transactions in secure places. Social network and routine activity markets provide a means for addressing these problems. Social network markets are those in which buyers only purchase from screened sellers or those recommended by a mutual acquaintance. This technique provides security in that buyers and sellers know one another and can be confident that the other party is not a representative of law enforcement. Furthermore, social network markets are hard to detect because they usually serve few buyers and are less likely to be located on street corners. Routine activity markets are open to a larger number of customers. They are usually found along major arterial routes, and demonstrate high place attachment. Such markets usually afford less protection due to their more open nature (Eck, 1995).

Open markets are described as similar to Eck's (1995) routine activity markets that are 'open' or available to all buyers willing to purchase a product. Sellers are able to maximize their customers' access by being in the same location on a regular basis, making them sensitive to the spatial pattern of demand. However, open markets make buyers and sellers vulnerable to policing because they are more likely to be located outdoors. Yet at the same time, certain areas (such as the Kings Cross commercial district in London) afford buyers and sellers protection due to the high population concentration and the inability to tell who is in the area for legitimate and illegitimate reasons (May & Hough, 2004).

Closed markets are similar to social network markets whereas both parties know one another (May & Hough, 2004). Sellers only sell to people they trust or to those who are vouched for through third parties. The risk of police apprehension is less than that of open markets, and buyers like closed markets due to the stability of supply, quality of drugs purchased, and trust between themselves and sellers. Furthermore, technology has changed the face of drug markets making them more flexible and convenient. Buyers and sellers can make appointments to meet at specified places using 'pay as you go' phones that don't retain a record of the user's home address or other details (Beckett, Nyrop, & Pfingst, 2006).

The operationalization of drug markets within criminal justice is just as varied if not more so than its conceptualization. A majority of research has focused on explaining why some areas have more drug-related arrests than others. For example, Taniguchi, Rengert, and McCord (2009) set out to determine whether drug markets demonstrate agglomeration effects similar to legitimate business firms. In other words, drug markets are viewed as businesses that cluster in space to appreciate benefits (intentionally or unintentionally) that would not be realized if they were more spatially dispersed. In their research drug markets were operationalized as a count of drug sales arrests in each of Philadelphia's 1,816 block groups from 2002 to 2003. Agglomeration was identified using a spatial lag variable to determine whether block groups with high drug sales arrests cluster near others with high drug sales arrests. They found that agglomeration was predictive of higher drug sales arrests within block groups, controlling for local demand, demographics, concentrated disadvantage, and land use correlates.

Other research has aggregated counts of drug sales arrests to block groups to explain changes in drug sales arrests over time (Robinson, 2008; Robinson & Rengert, 2006). The results of research by Robinson (2008) support the idea that drug markets can be defined within an economic framework, in that they involve exchanges where sellers position themselves closer to communities with more potential customers (geographic perspective) or closer to more disorganized communities (social disorganization perspective). In terms of policing from the economic perspective, interdiction of the most spatially advantageous site may displace sellers to slightly less advantageous locations.

Related research has examined the influence of demographics and criminal opportunity on the locations of drug markets by aggregating drug arrest counts to block groups (McCord & Ratcliffe, 2007). It appears that single female-headed households, poor educational attainment, and racial composition are positively related to drug arrest counts, while (surprisingly) housing tenure composition and male unemployment are negatively related to drug arrest counts.

Alternative spatial units such as census tracts have also been used to outline drug markets. Rengert, Chakravorty, Bole and Henderson (2000) argue that drug markets are sites where exchanges of drugs take place but their location depends on whether customers are local or regional. Retail marketing would suggest that dealers would want to locate near suspected drug-using populations. Research shows that such populations tend to be young, without a high school diploma, and unemployed. Using census data and operationalizing drug markets as the number of drug sales arrests per square mile of each census tract, they found that local drug markets tend to locate near tracts with the greatest proportions of young members, unemployed, with less than a high school education while regional markets tend to locate near highway on/off ramps.

While the use of census features is convenient, it draws concerns for over-inclusiveness as they are designed for census collection and not drug market delineation. In other words, when block groups and tracts are used as units of analysis, individual features in their entirety have the potential to take on the drug market characterization. This is unlikely to be an accurate representation of drug markets. Environmental criminology has revealed that hot spots of crime are not hot all the time, *and* that cold spots may be temporally intertwined within hot spots (Eck, Chainey, Cameron, Leitner, & Wilson, 2005). Thus high drug crime block groups or tracts may not have uniformly high drug activity within their units of analysis. The advantage of using such features is that they allow researchers to append census data, allowing for the control of sociodemographic factors by which communities vary.

Drug markets don't have to be identified using official arrest data or conform to census designated features. Oakland's Beat Health Program identified drug market locations using emergency call data and contacts from community organizations (Mazerolle, Kadleck, & Roehl, 1998; Mazerolle, Kadleck, & Roehl, 2004). Evaluations of the program took place at the street block level using surveys of place managers and on-site observations of social and physical disorder (Mazerolle, et al., 2004).

Additional research has moved beyond using census features. In the Jersey City Experiment, drug markets were defined as hot spots of crime by mapping narcotic sales arrests and drug-related emergency calls for service to street intersection areas (Weisburd

& Green, 1995). Researchers defined the hot spot areas by seeking input from narcotics detectives and then created market boundaries based on those data.

Sophisticated mapping techniques such as kernel density estimation (KDE) have also been used to define drug markets using arrest data (Lum, 2008). Using KDE, the locations of crime incidents are geocoded and clustering is determined by way of a mathematical algorithm examining the extent of weighted clustering within grids. A series of bandwidths are produced by the algorithm useful for creating a number of categories indicative of the extent of clustering. The user can then subjectively apply a ramp of colors to the categories for visual display of the extent of clustering across the space. This technique is problematic in that while it is aesthetically appealing, it has a tendency to suggest clustering in areas where it may not be taking place, due to the smoothing algorithm.

Recent research by Ratcliffe and Taniguchi (2009) and Taniguchi, Ratcliffe, and Taylor (2011) has also been influential in identifying drug markets. In their research, a drug market was conceptualized as street corners where known gang members were witnessed selling drugs. To investigate whether drug corners controlled by gangs are more violent than those not controlled by gangs, researchers constructed Theissen polygons around each corner in the city of Camden, New Jersey. The counts of drug incidents within polygons became the operationalization of drug markets.

Some have questioned how well arrest data are indicators of real drug activity. Warner and Coomer (2003) used a regression model that incorporated resident self-report surveys on the witnessing of drug activity as a predictor of official drug arrest data across

66 neighborhoods (block groups). They found that the survey measure was significant and positively associated with drug trafficking arrests, but demonstrated no real relationship with drug possession arrests. This suggests not only that respondents were able to distinguish trafficking from possession, but possibly that drug trafficking is a more visible and readily identifiable drug crime than possession. Other research at the city level has also supported the use of official drug arrest data, with construct validity tests indicating that they have strong relationships with public health data (Rosenfeld & Decker, 1999). Finally, Rengert, Ratcliffe and Chakravorty (2005) found that drug-related calls for service data co-varied with illegal drug arrests.

Journey to crime

While operationalizing drug markets is necessary in order to determine where they are located, such research does not indicate how far drug offenders travel to their offense locations. The distance traveled from an offender's starting point to the offense location is known as the journey to crime (Rengert, 2004). The criminal journey is a rational thought process governed by interests of efficiency, costs, and effort (among other things). Research and theory has suggested that the cognitive decision-making process is instrumental in determining multiple forms of human behavior and interaction. For example, criminology has given birth to general theory (Gottfredson & Hirschi, 1990), routine activity theory (Cohen & Felson, 1979), and the rational choice perspective (Cornish & Clarke, 1986), all of which describe offenders as logical and discerning who prefer convenient opportunities. However, these principles and ideas are subsumed under the least effort principle, a general theory of human behavior. "The Principle of Least Effort [is] the primary principle that governs our entire language and collective behavior of all sorts, including the behavior of our language and preconceptions" (Zipf, 1949, p. viii). More specifically, the least effort principle states that humans will select solutions that most effectively address the problem at hand as well as possible problems that may arise in the future. Considering this, one would expect that drug sellers would have an interest in identifying proximate client populations and that drug buyers would gravitate to nearby sellers.

Below, is a summary of the theoretical underpinnings of the journey to crime, including the least effort principle, routine activity theory, and crime pattern theory. This section then reviews research on journeys to crime, and journeys to drug crime specifically.

Least effort principle

Human functioning requires a constant selection of choices to accomplish predetermined objectives. What determines the selection of one choice relative to another is what is described as the principle of least effort (Zipf, 1949):

> In simple terms, the Principle of Least Effort means, for example, that a person in solving his immediate problems will view these against the background of his probable future problems, *as estimated by himself*. Moreover he will strive to solve his problems in such a way as to minimize the *total work* that he must expend in solving *both* his immediate problems *and* his probable future problems (Zipf, 1949, pp. 1, emphasis in original).

In other words, humans have a desire to minimize their energy expenditure such that the choice taken to accomplish an objective does not result in future wasted effort to compensate for the earlier, faulty approach.

Empirically and conceptually, researchers have shown applicability of the least effort principle to linguistics (Cancho & Sole, 2003), neighborhood cohesion (Hipp & Perrin, 2009), and crime (Rossmo, 2005; Wiles & Costello, 2000).

Routine activity theory

A number of interconnected theoretical propositions related to the least effort principle demonstrate specific applicability to journeys to crime including routine activity theory, and crime pattern theory. Cohen and Felson's (1979) macro-level routine activity theory argues that crime is the result of suitable targets, motivated offenders, and the absence of capable guardians converging in time and space during routine activity[2], suggesting that crime is not a function of well-developed planning, but the exploitation of ordinary opportunities.

The relevance of routine activity theory for this research is its recent modification that considers the significance of place managers. Place managers are those directly or indirectly responsible for supervising places (Eck, 1995). Indirect place managers include passers-by that may dissuade a potential offender due to their mere presence. Direct place managers are those directly charged with supervising an area, including store managers, police officers, and bouncers. Strong place management has the ability to exercise control and vigilance over a property, serving as a deterrent to potential drug dealers (Eck, 1994; Eck & Wartell, 1998, 1999; Mazerolle, et al., 1998). There are certain areas, however in which direct place management is likely to be weak. Examples include areas in and around parks, major transportation nodes, and busy intersections. The problem with such

[2] "Routine activity means any commonly occurring social activity providing for basic needs. Examples include formal work, leisure pursuits, obtaining shelter, child rearing, grocery shopping, and sleeping" (Williams & McShane, 2004, p. 238).

areas is that it's unclear who is directly responsible for activities occurring around and within them. The perceived lack of management and control over an area may serve as an opportunity for drug sellers (and subsequently drug buyers) to make illicit exchanges. In turn, if place management is indeed weak around public land uses, one would expect:

1. Drug dealers to compete in a possibly violent manner for turf in public markets due to the low likelihood of police detection.
2. Drug dealers to come from near and far distances due to the availability of customers brought by public land uses.
3. Drug buyers to travel from near and far distances due to the availability of drugs from multiple sellers.

In sum, crime takes place when suitable targets without place managers and motivated offenders without handlers converge in time and space (Felson, 1995). This convergence takes place within the realm of offenders and the law-abiding traversing to and from rudimentary activities. Within the context of drug markets however, neither buyers nor sellers are 'law-abiding' individuals. This presents a challenge for routine activity theory because in the case of drug crime, and contrary to the traditional model, there aren't any suitable targets *as defined by Cohen and Felson* (1979)—just two or more motivated offenders (buyers and sellers) seeking to make a transaction in an area of absent or poor place management. It is possible within the realm of drug crime to re-define the concept of a suitable target as one of two parties searching for the other to complete a drug transaction. In this sense, the routine activity crime triangle reflects two law violators carrying dual roles as suitable targets *and* motivated offenders, seeking one another during routine activity (Rengert, 2004).

Aside from the direct transactions that take place between buyers and sellers, the victimization of either can be understood within routine activity theory. For example, a person who recently purchased drugs from a dealer may become a suitable target for robbery by a motivated offender that witnessed the drug transaction. Drug dealers may be the target of robbery victimization by rival dealers. Based on routine activity theory, both situations are likely to take place in the absence of guardians and place managers.

Crime pattern theory

Offender search patterns for suitable targets are far from random, but likely to consider targets along major routes between central places of routine activity including the home, school, work, and places of recreation (Brantingham & Brantingham, 1993). The rudimentary nature of these activities suggests that trips to and from are likely to be relatively short and take place within the awareness space of offenders. Awareness space can be defined as the areas of which a person has any knowledge (Brown & Moore, 1970). Knowledge relating to one's awareness space is derived from direct and indirect contact. Awareness space defined by direct contact constitutes those areas of routine activity where individuals conduct daily tasks. Such places are also known as activity spaces (Rossmo, 2000) or routine activity spaces (Cohen & Felson, 1979).

Nodes, paths, and edges form the activity spaces of victims and offenders. Nodes are places that serve as the foci of daily life (Lynch & Rivkin, 1959). These places include the home, work, and other places that form the structure of one's common tasks (see Figure 1). Therefore, in the instance of drug buyers it is expected that many would purchase illicit substances within a convenient geography of the home. Other nodes may also provide opportunities for drug users depending on environmental characteristics. For example, a friend's home may provide the user with additional awareness space for which to search for a drug market. Conversely, the social tie with the friend may provide both with access to a drug market near the friend's home. The search patterns for drug sellers may also start near their respective homes, which are areas of which they are expected to have the most knowledge. In looking to set up drug markets however, and in line with routine activity theory, drug offenders are also likely to search initially around the home but for places that have poor place management.[3] Indeed, research for other offense types has shown that homicide (Bullock, 1955) and robbery offenses (Normandreau, 1968) tend to occur near offender residences.

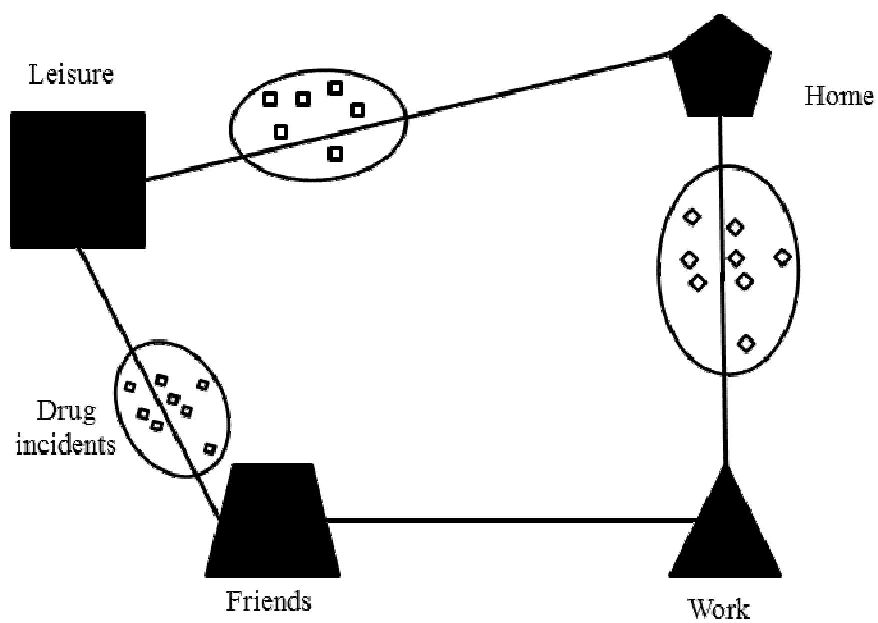

Figure 1: Crime pattern theory

Paths (indicated by the bold lines in Figure 1) are the routes that people take to move to and from their routine activities (Brantingham & Brantingham, 1995; Lynch &

[3] Of course, drug buyers are also likely to be concerned about place management as they are subject to police intervention. However, their choices are likely limited to the places that drug sellers that have been established as a buyer cannot purchase drug from an area where drugs are not being sold.

Rivkin, 1959). Because people spend considerable amounts of time traveling to and from activities, paths are important for forming knowledge about urban areas. Therefore, in addition to nodes, paths determine the areas that offenders search for targets, or in this case places for illicit drug exchanges. Therefore it is possible that routes to and from legitimate activities of drug offenders structure the location of drug markets.

The idea of pathways to criminal activity implies the existence of directional bias in offending. Research has shown that cities and downtown areas influence the direction of crime travel due to the opportunities afforded there (Erlanson, 1940; Hesseling, 1992; Rengert, 1996a, 2004; Wiles & Costello, 2000). In a study of the crime flow of Tel-Aviv, Israel, Rattner and Portnov (2007) found that 51% of crime was committed by local residents while the remaining proportion was composed of offenders traveling from surrounding areas. Burglars tend to victimize homes that are directionally aligned with their travel routes from home to work (Rengert & Wasilchick, 2000) indicating that potential offenders take advantage of opportunities that arise while traveling between routine activities. Furthermore, across multiple crime types offenders living in close proximity tend to travel in similar directions to offend, suggesting that criminal opportunities are not uniformly distributed across space (Costanzo, Halperin, & Gale, 1986).

Edges (physical and perceived) also tend to have effects on the travel patterns of offenders. These are areas that serve as borders between noticeably distinct areas (Brantingham & Brantingham, 1993, 1995). Physical edges include parks, rivers, and commercial strips, while perceived edges are those popularly characterized as delineating features between socially different communities. Perceived edges serve as invisible, yet largely impermeable boundaries, restricting robbery and burglary offenders to communities of their own race (Carter & Hill, 1976, 1979; Pettiway, 1982). It appears that offenders prefer to offend in communities that resemble their own sociodemographics so that they can blend into their surroundings without inviting suspicion (Brantingham & Brantingham, 1995; Rengert & Wasilchick, 2000).

In sum, crime pattern theory is a perspective on the site selection of offenders (Rossmo, 2000). Offenders do not select targets (or victims) at random but make calculated, rational choices based on a number of factors (Rengert, Piquero, & Jones, 1999). Because of this, target selection is based on a hedonistic calculus. Offenders are likely to commit crimes when the perceived benefits outweigh potential costs and risks (Cornish & Clarke, 1986) as presented by easy opportunities (Gottfredson & Hirschi, 1990). The search for criminal opportunities takes place in areas within and near the routine activity spaces of offenders. Therefore, in accordance with rational choice theory and the principle of least effort, offenders minimize their expended effort by first searching for opportunities in the areas that they know relatively well, which would include areas around major nodes and pathways of the activity space. These behaviors suggest that most journeys to the criminal event should possess short distances, with the likelihood of offending decreasing the farther one moves from the home. This is commonly known as the distance-decay function.

Distance-decay

The distance-decay function is an aggregate representation of travel distance to criminal offending in that criminal events generally occur close to offender residences and decrease exponentially the farther one moves from the residence (van Koppen & de

Keijser, 1997). In other words, the distance-decay function is the mathematical representation of the least effort principle, applied to criminal behavior. It can also be viewed as a mathematical travel distance representation of rational choice theory (Cornish & Clarke, 1986) and the general theory of crime (Gottfredson & Hirschi, 1990) as it clearly suggests that individuals are more likely to take advantage of easier, closer crime opportunities than ones farther away.

Nonetheless, although offenders are more likely to offend close to home than at farther distances, offenders tend not to offend *too* close to their home locations. "Within this zone, targets are viewed as less desirable because of the perceived risk associated with operating too close to home" (Rossmo, 2000, p. 120). Offenders tend to commit fewer crimes in these areas out of fears of recognition and association with criminal acts (Brantingham & Brantingham, 1993; Turner, 1969). Nonetheless, one should not assume that this buffer zone is crime free. It is merely an area immediately surrounding the offender's home where offending is *less* likely. Canter and Larkin (1993) reported a buffer zone for rape offenders of within .61 miles from the home. In a study using data from the Survey of State Prison Inmates, DeFrances and Smith (1994) reported that 52% of drug offenders, 72% of robbery offenders, and 69% of property offenders were incarcerated for offenses they committed outside their home neighborhoods.

Journeys to crime – Empirical research

Journeys to drug crime

<u>Pettiway (1995) study</u>

Pettiway (1995) studied a snowball sample of 160 predominately African American crack users in Philadelphia. Using a discriminant analysis he distinguished those who bought crack within their neighborhood (conceptualized as within .5 miles of the home) from those who traveled farther. Results indicated that males travel farther than females to purchase crack. Also, the number of children in the household, access to a vehicle, and the tendency to purchase crack outdoors were predictive of longer trips. Income was also predictive of distance traveled. As the proportion of a person's money generated illegally increased, their likelihood of traveling outside of their own neighborhood decreased. Season (winter) and the likelihood of buying drugs in one's own neighborhood were predictive of shorter trips suggesting that even when away from home, buyers return to familiar areas to purchase crack.

<u>Johnson, Taylor, and Ratcliffe (under review) study</u>

Using three years of arrest data (2005-2007) from the Camden (NJ) Police Department, Johnson, Taylor, and Ratcliffe (under review) examined variation in travel distance from home to arrest location for the purchase of illegal drugs. Three questions framed their research. First, how far do individuals travel to buy drugs, and does this vary by demographic correlates and drug choice? The work sought to extend earlier work on correlates by working with a more diverse sample of buyers, and, in addition, by controlling for specific location features. Second, do large agglomeration drug markets have longer customer reach, compared to less well known drug market locations? Third, if it looks like individual large markets rather than large markets as a class influence trip distance, what market factors might be relevant?

In accordance with other journey to crime research, the distance distribution of journeys to drug buying, like journeys to commit other types of crimes, is composed largely of relatively short distances. The median distance was .79 miles. And, in line with journey to crime research (Rengert, et al., 1999), the frequency distribution of the trip distances suggested a distance decay effect.

Placed in the context of journey to crime research, the authors' research confirmed that race mattered in the same way for journeys to buy drugs as it did for journeys to crime (Warren et al., 1998; Wiles & Costello, 2000). Whites traveled farther than African-Americans, even after controlling for differences in destination. The racial difference undoubtedly links in complex ways to both broader urban and suburban segregation patterns, as well as the spatially segregated pattern of drug market availability. In contrast to the journey to crime work generally, however, for journeys to buy drugs neither gender nor age proved relevant.

In relation to earlier work specifically on journeys to buy drugs, their findings confirmed longer trips to buy more expensive drugs, in this case heroin rather than marijuana. The influence of drug type sought on distance confirms Forsyth et al.'s (1992) UK finding, and extends it to a more racially, ethnically and locationally diverse US sample. It extends the earlier work on drug type and distance by showing the link held even after controlling for type of destination (market vs. non-market) and specific market destinations.

Prior to the work of Johnson and colleagues (under review) ethnicity has not been previously considered in the journey to buy drugs work. This work suggests it is important, with Hispanics traveling shorter distances on average than African Americans. Whether this is due to linguistic isolation, segregated settlement patterns, or interactions of these two with differential gang structures by ethnicity is not known. Hagedorn (1994) found outside white customers in Milwaukee seemed to prefer a Latino-run market over a potentially closer Black-run one. The shorter trip distances seen for Hispanics may have reflected their settlement concentration in northeast Camden, and the proximity of the Hispanic-run North Camden and Pyne Poynt markets. For a view of the locations of markets see Figure 1, page 37 in Johnson, Taylor, and Ratcliffe (under review).

When considering destination factors, the hypothesis that journeys ending in an identified market would be longer than those ending in locations not recognized as markets was not supported. Compared to non-market destination trips, market-destination trips were sometimes longer, and sometimes shorter. The only market whose trips were significantly different from the non-market destination average was that of Whitman Park. Located largely along and to the east of Mount Ephraim Avenue in southern Camden, the market is situated between census block groups that are in the top quintile for percent African-American. In addition to the simple proximity between the market's location and its sizable customer base, the high volume of marijuana sales relative to non-market locations also help explain the shorter trips to this market.

Police interdiction of local markets such as Whitman Park may be difficult based on the social ties among buyers and dealers who may have close-knit or temporally strong connections. Such connections may not only provide dealers and buyers with the time to create ties but to also develop social capital (Hipp & Perrin, 2009). In terms of illegitimate activity, social capital can be used as a resource to shield drug offenders from formal measures of social control, such as policing (Pattillo, 1998). For example, law-abiding residents of local markets may be hesitant about calling the police on drug buyers if they are a friend or neighbor's child (St. Jean, 2007). Thus, drug buyers *and* dealers may benefit from social capital and use it to their advantage to render drug transactions as a normative behavior within the neighborhood. The above arguments have significant implications for systemic social disorganization theory which argues that ties and capital are necessary to fight against crime. In other words, the same processes that theoretically allow law-abiding residents to prevent and address crime are the same processes that allow drug offenders to conduct illicit exchanges. If this is true, then the law-abiding residents may be too intertwined into networks with criminal offenders to address neighborhood drug markets, *even if they wanted to take action*. The extent to which the above possibly applies to the current study is explored later in the dissertation.

In short, although all market trips on average were not longer than non-market trips, results did suggest that in some instances specific market destination *did* influence distance even after taking drug and demographics into consideration. These distance differences may portend interdiction difficulties.

Two policy implications deserve mention. Results of the Johnson, Taylor, and Ratcliffe study underscore drug market variation. Some markets are local markets that serve neighborhood residents while others cater to a more regional clientele (Harocopas & Hough, 2005). Prevention policies may need to address those differences. For example in more localized markets social ties among buyers and dealers who may have close-knit ties creates social capital (Hipp & Perrin, 2009), lowers conflict (Reuter and MacCoun (1992) and makes interdiction and information-gathering more difficult. Second, some of these markets draw buyers from farther away, including suburban locations. As such, specific strategies can target just buyers in tailored ways. This was the approach in Philadelphia's Operation Fishnet (Dougherty, 1991). To address the problem of drug markets across the city, local, state, and federal law enforcement engaged in an inter-agency effort to conduct surveillance and arrest drug sellers engaging in illicit street-level drug transactions. Drug buyers were also arrested; however, non-residents of Philadelphia that drove to the market were also subject to vehicle confiscation.

In sum, drug-buying trip distance was analyzed for a multi-racial, multi-ethnic sample of metropolitan buyers purchasing a range of drugs and taking drug, buyer, and destination features into account. Race and drug type were found to have significant effects on trip distance, even after controlling for destination. The study by Johnson and colleagues (under review) is the first study to find impacts of ethnicity (Hispanic) on drug buying trip distance. Distances for trips ending in one market were significantly different from distances for non-market trips, and gang market involvement roughly aligned with distances in ways supportive of earlier theory.

Offender journeys to crime

Other journey to crime literature has found a number of consistent themes, all of which support that offenders adhere to the least effort principle. First, in spite of offenders across all crime types traveling relatively short distances to offend, there is some variation by crime type. For example, in a study of Indianapolis homicides White (1932) found that offenders travel a mean distance of .11 miles to the offense location.[4] Longer—albeit still short—distances of under 1 mile were reported by other studies (Bullock, 1955; Gabor & Gottheil, 1984; Groff & McEwen, 2006). Less lethal person offenses such as aggravated assault also result from short offender travel distances,

[4] White (1932) was the only study to measure distance as the length between the centroid of the offender's home census tract and the offense location census tract. All other studies calculated distance as the length between the home and incident location (unless otherwise stated).

generally less than 1 mile (Block, Galary, & Brice, 2007; Gabor & Gottheil, 1984; Phillips, 1980; White, 1932). Studies of sexual assault have found substantial variation in travel distance, with findings ranging from .07 miles to over 3 miles (Amir, 1971; Block, et al., 2007; Canter & Larkin, 1993; Gabor & Gottheil, 1984; Rhodes & Conly, 1981; Warren, et al., 1998). Research generally reports lengthier travel patterns for robbery offenders. In a study of Philadelphia robbers, Normandreau (1968) reported a mean travel distance of 1.07 miles. However, other research has found that robbers are willing to travel substantially farther with mean distances over 2 miles (Nichols, 1980; Rhodes & Conly, 1981; White, 1932).

Although residential burglary tends to be a more calculated crime, such offenders also travel short distances (Wiles & Costello, 2000). Bernasco and Block (2009) found that Chicago burglars are 822 times more likely to burglarize a home within their residence census tract and 99 times more likely to burglarize one in an adjacent census tract than one 5 borders away. There is however, a positive relationship between the distance traveled and the value of goods stolen, suggesting that burglars possess a willingness to travel if the anticipated rewards are substantial (Snook, 2004). Ratcliffe (2001) reported that residential burglars in Canberra, Australia travel a mean distance of 3.11 miles while nonresidential burglars travel a mean of 3.04 miles. Research of Helsinki, Finland burglars found a mean travel distance of slightly under 2.5 miles. Scholars conducting studies of burglary in American cities have found burglars travel between 1 and about 1.75 miles (Phillips, 1980; Rhodes & Conly, 1981; Snook, 2004; White, 1932) with the exception of one reporting findings of ½ mile (Reppetto, 1976).

From the above findings, it appears that personal offenses such as homicide and aggravated assault are the result of short travel distances. Personal crimes such as homicide usually take place between those familiar with one another, or those living in close proximity and are the result of heated disagreements between parties (White, 1932). These crimes take place under intense situations where the decision to commit the criminal act is made in a matter of seconds (Collins, 2008) compared to property crimes that involve some planning on behalf of offenders. Property offenders compared to violent offenders involved in passionate-intense moments have to search for criminal opportunities (Reppetto, 1976) which may partially explain why they travel so far to offend. Indeed, White (1932) found that the average distance traveled to commit crimes against persons was .84 miles compared to 1.72 miles for those crimes committed against property. Table 1 summarizes the trip distances reported by research cited in this dissertation.

A second theme finds that across multiple crime types, older offenders travel farther than younger ones (Gabor & Gottheil, 1984; Groff & McEwen, 2005; Nichols, 1980; Snook, 2004; Warren, et al., 1998). This finding isn't surprising considering that juvenile mobility is limited by the inability to drive, and smaller awareness space. However, one study did find travel distance to increase from ages 10 to 19, decline until age 55, and then increase again around 60 years of age before steadily declining (Chainey, Austin, & Holland, 2001).

Third, there are significant gender impacts with males traveling farther than females to offend (Gabor & Gottheil, 1984; Groff, Wartell, & McEwen, 2001; Nichols, 1980; Pettiway, 1995) suggesting that women may be constrained by childrearing activities that prevent them from venturing too far from the home. However, one study did find female juvenile offenders to travel farther than males (Phillips, 1980). A possible explanation is that females were co-offenders with older males with larger awareness spaces, and therefore capable of making longer trips to offend.

Lastly, whites travel farther than minorities to offend (Carter & Hill, 1979; Nichols, 1980; Pettiway, 1982, 1995; Warren, et al., 1998; Wiles & Costello, 2000). The relative socioeconomic status of minorities relative to whites may render them less likely to own a vehicle and constrain the distance they can travel at ease to offend. Pettiway (1995) reported that those with vehicles were more likely to travel outside of their neighborhoods to offend.

Table 1: Travel distance by crime type

Crime	Location/Time Period	Trip distance in miles	Measurement	Source
All offenses	Rochester, NY (1972)	1 (mean)	Unknown	Smith (1976)
Assault	Chicago, IL (1998)	victims: .01 (median), Offenders: .11 (median)	Manhattan	Block et al. (2007)
Assault	Ottawa, Canada (1981)	1.33 (mean)	Euclidean	Gabor & Gottheil (1984)
Assault	Indianapolis, IN (1930)	.91 (mean)	Unknown	White (1932)
Assault	Lexington-Fayette, KY (1974-1975)	.7 (mean)	Unknown	Phillips (1980)
Auto banditry	Indianapolis, IN (1930)	3.43 (mean)	Unknown	White (1932)
Burglary	Ottawa, Canada (1981)	.35 (mean)	Euclidean	Gabor & Gottheil (1984)
Burglary	Greater Helsinki Area, Finland (2001)	2.41 (median)	Euclidean	Laukkanen, Santtila, Jern, & Sandnabba (2008)
Burglary	Unknown	.5 (mean)	Unknown	Reppetto (1976)
Burglary	St. John's, Canada (1989-1999)	1.06 (median)	Unknown	Snook (2004)
Burglary	Indianapolis, IN (1930)	1.76 (mean)	Unknown	White (1932)
Burglary	Sheffield and North Yorkshire, UK	1.88 (mean)	Euclidean	Wiles & Costello (2000)
Burglary	Washington, DC	1.62 (mean), 1.2 (median)	Street network	Rhodes & Conly (1981)
Burglary	Lexington-Fayette, KY (1974-1975)	1.05 (mean)	Unknown	Phillips (1980)
Burglary (non-residential)	Canberra, Australia (1999 - 2000)	3.04 (mean)	Unknown	Ratcliffe (2001)
Burglary (residential)	Canberra, Australia (1999 - 2000)	3.11 (mean)	Unknown	Ratcliffe (2001)
Burglary (residential)	London Borough of Harrow, UK (1997-2001)	1.21 (mean)	Euclidean	Chainey et al. (2001)
Burglary (residential)	London Borough of Harrow, UK (1997-2001)	1.85 (mean)	Street network	Chainey et al. (2001)
Burglary (residential)	London Borough of Harrow, UK (1997-2001)	1.56 (mean)	Manhattan	Chainey et al. (2001)

Table 1, continued: Travel distance by crime type

Check fraud	Ottawa, Canada (1981)	1.74 (mean)	Euclidean	Gabor & Gottheil (1984)
Disorderly conduct	Lexington-Fayette, KY (1974-1975)	1.06 (mean)	Unknown	Phillips (1980)
Drugs (possession)	Camden, NJ (2005-2007)	1.04 (mean), .6 (median)	Manhattan	Ratcliffe & Johnson (under review)
Drugs (possession)	London Borough of Harrow, UK (1997-2001)	1.23 (mean)	Euclidean	Chainey et al.
Drugs (possession)	London Borough of Harrow, UK (1997-2001)	1.73 (mean)	Street network	Chainey et al. (2001)
Drugs (possession)	London Borough of Harrow, UK (1997-2001)	1.59 (mean)	Manhattan	Chainey et al. (2001)
Drugs related	Lexington-Fayette, KY (1974-1975)	1.93 (mean)	Unknown	Phillips (1980)
Embezzlement	Indianapolis, IN (1930)	2.79 (mean)	Unknown	White (1932)
Homicide	Washington, DC (1992-2002)	victims: .54 (median), Offenders: .74 (median)	Euclidean	Groff & McEwen (2005)
Homicide	Washington, DC (1992-2002)	victims: .69 (median), Offenders: .92 (median)	Street network	Groff & McEwen (2005)
Homicide	Houston, TX (1945-1949)	victims: 75% < 1 , Offenders: 67% < 1	Unknown	Bullock (1955)
Homicide	Ottawa, Canada (1981)	.54 (mean)	Euclidean	Gabor & Gottheil (1984)
Homicide	Indianapolis, IN (1930)	.11 (mean)	Unknown	White (1932)
Larceny (grand)	Indianapolis, IN (1930)	1.53 (mean)	Unknown	White (1932)
Larceny (grand)	Lexington-Fayette, KY (1974-1975)	1.31 (mean)	Unknown	Phillips (1980)
Larceny (petty)	Indianapolis, IN (1930)	1.42 (mean)	Unknown	White (1932)
Larceny (petty)	Lexington-Fayette, KY (1974-1975)	2.46 (mean)	Unknown	Phillips (1980)
Loitering	Lexington-Fayette, KY (1974-1975)	1.65 (mean)	Unknown	Phillips (1980)
Obtaining money falsely	Indianapolis, IN (1930)	1.47 (mean)	Unknown	White (1932)
Personal crime	Cleveland, OH (1973-1975)	2.3 (mean)	Unknown	Pyle (1976)

Table 1, continued: Travel distance by crime type

Property crime	Cleveland, OH (1973-1975)	1.93 (mean)	Unknown	Pyle (1976)
Public intoxication	Lexington-Fayette, KY (1974-1975)	1.37 (mean)	Unknown	Phillips (1980)
Racial offenses	London Borough of Harrow, UK (1997-2001)	0.67 (mean)	Euclidean	Chainey et al. (2001)
Racial offenses	London Borough of Harrow, UK (1997-2001)	0.97 (mean)	Street network	Chainey et al. (2001)
Racial offenses	London Borough of Harrow, UK (1997-2001)	0.9 (mean)	Manhattan	Chainey et al. (2001)
Robbery	Miami, FL (1971)	33% < 1 , 50% < 2 , 2/3 < 3	Euclidean	Capone & Nichols (1976)
Robbery	Philadelphia, PA (1960-1966)	victims: 1.61 (median), Offenders: 1.07 (median)	Unknown	Normandreau (1968)
Robbery	Unknown	.6 (mean)	Unknown	Reppetto (1976)
Robbery	Indianapolis, IN (1930)	2.14 (mean)	Unknown	White (1932)
Robbery	Dade County, FL (1975)	2.02 (mean) for those < 20 years old, 4.98 for those > = 20 years; 2.29 (mean) blacks, 6.67 (mean) whites; 3.56 (mean) males, 2.45 (mean) females	Euclidean	Nichols (1980)
Robbery	Washington, DC	2.1 (mean), 1.62 (median)	Street network	Rhodes & Conly (1981)
Robbery	London Borough of Harrow, UK (1997-2001)	1.47 (mean)	Euclidean	Chainey et al. (2001)
Robbery	London Borough of Harrow, UK (1997-2001)	1.94 (mean)	Street network	Chainey et al. (2001)
Robbery	London Borough of Harrow, UK (1997-2001)	1.89 (mean)	Manhattan	Chainey et al. (2001)
Robbery (armed)	Ottawa, Canada (1981)	1.22 (mean)	Euclidean	Gabor & Gottheil (1984)

Table 1, continued: Travel distance by crime type

Robbery (non-commercial)	Chicago, IL (1998)	victims: .4 (median), Offenders: .8 (median)	Manhattan	Block et al. (2007)
Robbery (unarmed)	Ottawa, Canada (1981)	.62 (mean)	Euclidean	Gabor & Gottheil (1984)
Sex offenses	London Borough of Harrow, UK (1997-2001)	0.81 (mean)	Euclidean	Chainey et al. (2001)
Sex offenses	London Borough of Harrow, UK (1997-2001)	1.06 (mean)	Street network	Chainey et al. (2001)
Sex offenses	London Borough of Harrow, UK (1997-2001)	0.97 (mean)	Manhattan	Chainey et al. (2001)
Sexual assault	Chicago, IL (1998)	victims: .33 (median), Offenders: .07 (median)	Manhattan	Block et al. (2007)
Sexual assault	Greater London, South East UK (1980s)	1.53 (mean minimum distance)	Unknown	Canter & Larkin (1993)
Sexual assault	Ottawa, Canada (1981)	1.43 (mean)	Euclidean	Gabor & Gottheil (1984)
Sexual assault	Unknown	3.14 (mean); closest mean: 1.7, farthest mean: 4.9	Manhattan	Warren et al. (1998)
Sexual assault	Indianapolis, IN (1930)	1.52 (mean)	Unknown	White (1932)
Sexual assault	Philadelphia, PA (1958-1960)	In 82% of cases, offenders and victims lived 5 blocks of one another. In 68% of cases, offenders lived within 5 blocks of the offense and the victim. In 26% of cases offenders resided > 5 blocks from victim and offense location.	N/A	Amir (1971)
Sexual assault	Washington, DC	1.15 (mean), .37 (median)	Street network	Rhodes & Conly (1981)

Table 1, continued: Travel distance by crime type

Shoplifting	London Borough of Harrow, UK (1997-2001)	1.68 (mean)	Euclidean	Chainey et al. (2001)
Shoplifting	London Borough of Harrow, UK (1997-2001)	2.18 (mean)	Street network	Chainey et al. (2001)
Shoplifting	London Borough of Harrow, UK (1997-2001)	2.18 (mean)	Manhattan	Chainey et al. (2001)
Theft	London Borough of Harrow, UK (1997-2001)	1.2 (mean)	Euclidean	Chainey et al. (2001)
Theft	London Borough of Harrow, UK (1997-2001)	1.64 (mean)	Street network	Chainey et al. (2001)
Theft	London Borough of Harrow, UK (1997-2001)	1.49 (mean)	Manhattan	Chainey et al. (2001)
Theft (over $200)	Ottawa, Canada (1981)	1.74 (mean)	Euclidean	Gabor & Gottheil (1984)
Theft (under $200)	Ottawa, Canada (1981)	1.19 (mean)	Euclidean	Gabor & Gottheil (1984)
Theft from vehicle	London Borough of Harrow, UK (1997-2001)	0.69 (mean)	Euclidean	Chainey et al. (2001)
Theft from vehicle	London Borough of Harrow, UK (1997-2001)	1.41 (mean)	Street network	Chainey et al. (2001)
Theft from vehicle	London Borough of Harrow, UK (1997-2001)	1.12 (mean)	Manhattan	Chainey et al. (2001)
Theft of vehicle	Ottawa, Canada (1981)	1.24 (mean)	Euclidean	Gabor & Gottheil (1984)
Theft of vehicle	Lexington-Fayette, KY (1974-1975)	1.15 (mean)	Unknown	Phillips (1980)
Theft of vehicle	London Borough of Harrow, UK (1997-2001)	1.48 (mean)	Euclidean	Chainey et al. (2001)
Theft of vehicle	London Borough of Harrow, UK (1997-2001)	2.05 (mean)	Street network	Chainey et al. (2001)
Theft of vehicle	London Borough of Harrow, UK (1997-2001)	1.8 (mean)	Manhattan	Chainey et al. (2001)
Theft of vehicle	Indianapolis, IN (1930)	1.77 (mean)	Unknown	White (1932)

Table 1, continued: Travel distance by crime type

Theft of vehicle	Sheffield and North Yorkshire, UK	2.36 (mean)	Euclidean	Wiles & Costello (2000)
Vandalism	London Borough of Harrow, UK (1997-2001)	1.04 (mean)	Euclidean	Chainey et al. (2001)
Vandalism	London Borough of Harrow, UK (1997-2001)	1.51 (mean)	Street network	Chainey et al. (2001)
Vandalism	London Borough of Harrow, UK (1997-2001)	1.32 (mean)	Manhattan	Chainey et al. (2001)
Vandalism	Lexington-Fayette, KY (1974-1975)	1.31 (mean)	Unknown	Phillips (1980)
Violent crime	London Borough of Harrow, UK (1997-2001)	0.77 (mean)	Euclidean	Chainey et al. (2001)
Violent crime	London Borough of Harrow, UK (1997-2001)	1.09 (mean)	Street network	Chainey et al. (2001)
Violent crime	London Borough of Harrow, UK (1997-2001)	0.99 (mean)	Manhattan	Chainey et al. (2001)

Victim journeys to crime

Research has also considered victim journeys to crime. Victim journeys to crime are typically operationalized as the travel distance from the victim's home to the incident location. However, it is not in the interest of this dissertation to conduct a thorough review of victim journeys to crime as the applicability of victim journeys to this research is questionable. When considering exclusively those involved in illicit drug exchanges and barring negative externalities, there are no real victims. Two motivated offenders are merely seeking one another to engage in a victimless crime. On the other hand, the negative externalities associated with the drug trade such as violence is one of the most salient concerns of drug market research. Therefore, it may be that victims not involved in the drug trade yet residing in a community with an outdoor drug market may suffer from direct and indirect exposure to violence relative to the drug trade. In turn, the proximity of even the law-abiding victim's home to the drug market may have implications for understanding the journey to crime.

Scholarship on victim journeys to crime has uniformly confirmed that victimization takes place close to home (Amir, 1971; Block, et al., 2007; Bullock, 1955; Groff & McEwen, 2005; Normandreau, 1968; Rand, 1986; Tita & Griffiths, 2005). When comparing journeys by crime type, it appears that homicide victims travel the least distance to the incident location, well under one mile (Block, et al., 2007; Groff & McEwen, 2005). It is likely that such person offenses take place between intimate partners living together or those who come in frequent contact with one another, rather than strangers. Sexual assault victimization also takes place at or very near the victim's home (Amir, 1971; Block, et al., 2007) lending support the findings that sexual victimization tends to take place among familiar individuals. Victims appear to travel farthest to robbery locations with a median distance of 1.61 miles according to one study (Normandreau, 1968), yet other researchers have produced findings of less than ½ mile. Overall victims travel less far than their offenders. However, Normandreau (1968) found the opposite in a study of Philadelphia robbery journeys.

The above indicates that overall, offenders and victims travel short distances to offense locations, but it also suggests that they live close to one another. Pokorny (1965) found that in 73% of homicide cases victims and offenders lived within 1 mile of one another. Yet, even after removing cases of intimate partners living at the same address from the analysis, 43% incidents occurred between offenders and victims living less than ⅓ mile apart. Amir (1971) reported that in 82% of sexual assault cases victims and offenders lived within 5 blocks of one another. Similar findings were reported by Tita and Griffiths (2005) and Groff and McEwen (2006).

In summary, the journey to crime literature shows that:

- Overall, the criminal journey to crime is short;
- Violent and person offenses are likely to have the shortest offending distances when compared to residential burglary;
- Little research has explored the travel distances of drug offenders.

With the above in mind, the following section considers a theory that draws a connection between the travel distances of drug offenders and violence within drug markets.

Reuter and MacCoun's theory of drug markets and violence

While it is interesting to understand the commuting patterns of drug dealers to working locations and drug buyers to street drug retail outlets, an even more interesting and practically-oriented inquiry involves how the travel distance of drug buyers and sellers to drug markets impacts the surrounding community. This dissertation asks: Does the travel distance of drug offenders have implications for market dynamics that fuel or suppress violence? Reuter and MacCoun's (1992) typology of drug markets suggests that this certainly may be the case in arguing that the economic nature of drug markets, dictated by their geographic influences has implications for the conflicts they facilitate:

> … each market drains the human capital of the neighborhood to the extent that residents are exposed to the risks of addictive drug use, incarceration, and illicit activities that may interfere with schooling and legitimate work. However, the markets differ in the flow of cash for retail sales, and we believe that they also differ in their economic effect, the violence they engender, and in their responsiveness to policy initiatives (p. 237).

Considering the above, Reuter and MacCoun (1992) conceptualized four different categories of drug markets based on the travel patterns of dealers and buyers: local, export, import, and public. A discussion of those categories is presented below. The original article, as well as Reuter's (2000) National Institute of Justice Drug Market Conference paper titled "The Measurement of Local Drug Markets," provides little in terms of theoretical or empirical explanations of the four categories; however, additional literature provides some support.

Local markets

Local drug markets are characterized by buyers and dealers who tend to be residents of the local neighborhood (Reuter, 2000). Because money exchanges hands among neighborhood residents rather than outside residents bringing money into the community through the purchase of drugs, these communities tend not to gain much economically from the drug market. Local markets, therefore serve as suppliers for the needs of local drug-addicted residents. The familiarity of buyers and dealers with the local community allows such markets to relocate as necessary to avoid police interdiction. These markets are expected by Reuter and MacCoun to be the least violent because participants are likely to have established mechanisms of informal social control along with sustaining relationships. "… [L]ocal markets may be the least harmful precisely because the participants are well acquainted and violence risks retribution" (Reuter, 2000, p. 9).

Research has yet to empirically explore the dynamics of local markets. Research on social ties and physical distance however, does shed some light on this category (Conley & Topa, 2002; Mesch & Levanon, 2003). Hipp and Perrin (2009) examined the influence of social and physical distance on the formation of ties among neighbors in a community in the southern region of the United States. It is easier for individuals to form ties if they live within close spatial proximity than if they lived farther apart (Zipf, 1949). Social distance (or the relative difference among individuals) can prevent the formation of social ties because it reduces shared interests among individuals, inhibits the formation of group identity, and re-enforces role and lifestyle differences such as those implied by marital status (Hipp & Perrin, 2009).

Hipp and Perrin mailed five-item surveys to residents asking them to identify neighbors with whom they have various forms of contact, operationalized as close and weak ties[5] (Hipp & Perrin, 2009). Researchers found that physical distance reduces the likelihood of weak or strong ties forming, suggesting the importance of accounting for spatial proximity when estimating social tie formation. The authors simultaneously found that social distance along with wealth reduces the likelihood of weak ties forming. Social distance on life course markers such as age, marital status, and the presence of children reduces the formation of weak ties. Consistent with the systemic model of social disorganization theory, each additional month of shared residence in the neighborhood increases the likelihood of forming both weak and strong ties.

Such findings lend support to Reuter and MacCoun's (1992) local drug market category. Hipp and Perrin (2009) would argue that when community residents are of similar social backgrounds, they are more likely to be able to form ties with one another. This category suggests a close-knit community whereby bonds are perhaps temporally strong and based on neighborhood loyalty. These long-standing connections may provide local drug dealers and buyers with the time not only to establish social ties but to develop social capital (Hipp & Perrin, 2009). Within the context of illegitimate activity, social capital is used as a resource to shield offenders from more regulatory forms of social control (such as police intervention) (Pattillo, 1998). Even if community members were interested in addressing drug offenders in local markets, it would be difficult to do so because the criminal is too intertwined in legitimate social networks for informal social control to have a regulatory effect against them. For example, residents of drug dealing communities may be apprehensive about calling the police on drug dealers if it is a friend

[5] Hipp & Perrin (2009) define weak ties as those where neighbors talk to one another, visit each other's homes, and communicate via email or phone. Close ties are those where a neighbor reports that they feel close to another neighbor.

or neighbor's child (St. Jean, 2007). Therefore, offenders benefit from social capital and are able to use informal social control to their advantage to instill norms for drug transactions within the neighborhood. It's these dynamics which are likely to suppress conflict and violence among drug buyers, dealers, and the community.

Export markets

In export drug markets, local dealers sell to those living outside of the neighborhood. Reuter and MacCoun (1992) describe these as "drive-through" markets. Economically speaking, these drug markets bring outside money into socioeconomically depressed neighborhoods on behalf of suburban drug buyers (Johnson, et al., under review). This argument is supported by St. Jean's (2007) description of a Bronzeville, Chicago drug market:

> The drug clientele is very diverse. It includes unemployed street hustlers and addicts, blue-collar workers, college students, and professionals. Some of these clients live on Grand Boulevard, but most reside in other areas and travel there only to purchase drugs. In a neighborhood that is predominantly African American, many white clients can be seen making drug purchases, and then heading back to the Dan Ryan Expressway, north toward downtown, or south to Hyde Park (p. 101).

The drug economy serves to fill a void and provides illicit employment opportunities in communities where legitimate employment opportunities are few or nonexistent. Structural changes throughout the 1960s and 70s, such as the flight of low-skill industrial jobs, created a jobs-skills spatial mismatch whereby inner-city minorities were no longer qualified for the high skill positions replacing low-skill jobs in the central city (Wilson, 1996). The sale of drugs and the relative normalcy in many communities of that behavior is an adaptation to structural changes in the availability of jobs and the realization by many residents that their opportunities to acquire middle-class status through legitimate means are largely limited (Anderson, 1999). It is possible that in the communities of such markets, residents may perceive that the economic benefit of drug dealing exceeds the negative aspects commonly associated with it. In a study of the economic nature of Manhattan drug markets, Fagan (1992) found that because "… neighborhood residents benefit from the secondary economic demand generated by drug selling, this undercuts efforts at formal and informal social control. Residents are likely to be less willing to disrupt drug selling when they directly benefit from it" (p. 135). Indeed, St. Jean (2007) found that drug dealing organizations in Chicago were known to use their profits to fund civic activities for the local community.

Dealers have a strong interest in suppressing violence within these markets. Violence and other illicit activity arguably brings the attention of law enforcement, which can reduce the profitability of drug markets (Venkatesh, 2008), especially if suburban patrons feel threatened by it. Additionally, dealers possess an affinity to their neighborhoods due to familial and social attachments (Pattillo, 1998). Therefore, in spite of their illegal behavior they have a strong altruistic interest in isolating local friends and family members from violence (Pattillo, 1998). This indicates that efforts to suppress violence are instrumental in maintaining good business not only for the sake of profits, but also for protecting loved ones from conflicts that may arise due to drug activity.

Import markets

Import markets (also described as parasitic markets) are those where nonresident dealers sell to neighborhood residents (Reuter & MacCoun, 1992). Import markets drain neighborhoods economically because residents are buying from sellers who are not invested (or residing) in the local community. Therefore, residents of import market communities are expected to cooperate more with the police. The dynamics of import markets create conditions favorable for violence, because the lack of investment in the local community on behalf of sellers and their perceived anonymity make such dealers more likely to result to violence to settle disputes. These dealers are likely to conflict with other dealers, as well as neighborhood residents who detest their presence. Reuter (2000) expects these markets to be the most violent out of the four.

The most vivid example of import drug markets is shown by Pattillo's (1998) analysis of drug dealers from the Groveland community in Chicago traveling to other communities to sell drugs:

> The money is to be made elsewhere, outside of Groveland. One ex-dealer reports, "I'll say all the people over here go to the other side [of the railroad tracks] to sell drugs. That's where all the places to do it. They'll go on the other side." The proximity of Groveland to low-income markets attests to the primacy of geography in explaining crime in Groveland. Like the residents in Groveland who commute to their legal jobs, Groveland's drug dealers do most of their business outside of the neighborhood, but the violent repercussions of the drug trade often spill over into their own territory (p. 768).

Pattillo (1998) argues that although dealers may not have a caring attitude toward the communities of which they sell, they do care about their home communities. Drug dealers from middle-class communities may decide to sell elsewhere out of respect for the values they learned while growing up in their own communities. Dealers from Groveland desire safe conditions for their children and reportedly instill middle-class values in their children. Yet as mentioned earlier, the protection that the gangs provide for the greater community is due to the drug economy of which they participate. "If no gangs existed, there would be no need for the protection that gangs provide. The same logic holds for the coordinated, yet competitive, sale of drugs" (Pattillo, 1998, p. 769). This suggests that the deleterious effects that drug dealers avoid by traveling outside of their home communities to conduct business may in fact follow them back home to haunt them.

Other evidence suggests that import drug markets result in violence within the drug market community. Philadelphia media reports have documented that college students attempting to sell drugs within local communities have been met with violence, as this may be seen as a sign of disrespect and territory encroachment by local resident drug dealers (Gambacorta, 2010).

Rasmussen, Benson, and Sollars (1993) argue that changes in drug control policies result in dealers traveling outside of their home jurisdictions to avoid stronger penalties. In a study of drug and violent crime across Florida counties, they found that increases in the proportion of drug arrests in a particular county relative to total arrests in surrounding counties leads to the displacement of sellers to counties where the penalties for drug dealing are perceived to be less severe, and increased violent crime as a result.[6] Profitable drug markets in and of themselves are likely to engender violence because they are constantly sought after by competing dealers. However, law enforcement contributes to the drug market violence by disrupting markets and forcing sellers to compete with rival sellers for fewer drug dealing locations. Violence also takes place due to the influx of new drug dealers into the drug market and the targeting of drug dealers as robbery victims as a result.

[6] Rasmussen, Benson, and Sollars (1993) failed to adequately control for spatial lag effects. Recent research addressing this problem has shown that targeted enforcement of drug markets resembling agglomeration economies does not lead to significant displacement but a diffusion of benefits (Taniguchi, Rengert, & McCord, 2009).

Public markets

In public markets, neither sellers or buyers are residents as transactions are likely to take place in public areas such as transit stations, schools and parks (Reuter & MacCoun, 1992). Eck (1995) described such locations as routine activity markets that also align major arterial routes and tend to be fixed to those areas over time. In these markets buyers and dealers are less likely to know one another, and as a result buyers rely on dealers being in the same location in order to make transactions. The anonymity involved in public markets can breed paranoia and causes conflict between sellers and buyers. Furthermore, dealers are likely to compete with other dealers for these locations because they tend to be in areas with substantial foot traffic for access to potential customers. In turn, Reuter and MacCoun describe these as violent markets. Public area markets also provide anonymity because buyers and sellers are able to blend into the surroundings giving the perception that they are in the area for legitimate reasons (Eck, 1995). If such markets are interdicted by police they may find difficulty restarting in another location (Reuter, 2000; Reuter & MacCoun, 1992).

A number of researchers have described what Reuter and MacCoun (1992) have termed public markets, albeit under different labels. Descriptions relative to public markets by May and Hough (2004) and Eck (1995) have been described elsewhere in this literature review. St. Jean (2007) however, provides an adaptation of Eck's (1995) routine activity markets; his conceptualization is summarized below.

According to St. Jean (2007), drug dealers prefer to conduct business in areas that are ecologically advantageous. Drug dealers prefer locations where they can conduct secure transactions. These areas tend to be major intersections that attract plenty of foot traffic to patron local businesses such as grocery stores and liquor stores. Therefore, certain land uses promote illegitimate opportunities for drug dealing because of the amount of people that seek those locations to carry out routine activities. According to Brantingham and Brantingham (1995) these areas serve as crime generators and attractors. They are crime generators in the sense that they naturally bring together large numbers of law abiding individuals to carry out simple tasks. On the other hand, they act as attractors because offenders (in this case drug dealers and buyers) seek out these locations to exploit the opportunity to conduct drug transactions there.

Busy locations also allow for drug dealers and buyers to engage in drug transactions while giving the impression that they are there for legitimate reasons (Eck, 1995). St. Jean (2007) refers to this component of ecological advantage as deniability:

> The ability to deny that one is in a location to sell or purchase drugs is the second ecological advantage drug dealers seek in micro locations in which to conduct sales. Such locations are often at or close to busy intersections, commercial strips, bus stops, corner stores, liquor stores, barber shops and beauty salons, fast-food outlets, housing complexes, parks, playgrounds, and school yards. The crowds in these locations sometimes provide opportunities for drug dealers to blend in and conduct secret transactions. However, if the dealers seem suspicious and are approached by police, they can tell a convincing lie about why they are there, since those areas have other, legitimate purposes (p. 124).

Drug dealing interviewees reported that when accosted by the police, they state that they are in such locations to wash clothes, wait on the bus or for an associate to give them a ride to work, buy a soda or snack, or visit a loved one (St. Jean, 2007). Additionally, interviews of police officers conducted by the author during the summer of 2009 in Philadelphia revealed that local drug dealers and buyers often provide similar deniability excuses.

Lastly, drug markets are expected to locate near those willing to store their drugs and money (St. Jean, 2007). Drug dealers prefer not to carry their entire stash of drugs on them throughout the workday as they run the risk of arrest. Carrying minimal amounts of drugs and money while stashing the bulk elsewhere minimizes the risk involved in drug dealing. This suggests that not only do dealers prefer to deal in busy locations that afford deniability and secure transactions, but that their drug source locations are not very far away. Close storage locations allow drug dealers to minimize the time, energy, and money spent on re-stocking drugs for sale. These storage facilities tend to be the homes of relatives or lovers. Many times, dealers pay a local resident of whom they are acquainted to hold drugs for them. In socioeconomically-depressed communities, stashing drugs is another way that local residents gain income from the illegitimate drug economy. Because drug dealers are accessing social capital nearby public markets to sustain their drug operations, it is possible that they too live near public drug markets. Recall that Hipp and Perrin (2009) found that physical proximity was a significant predictor for the formation of social ties, which may serve as the prelude to developing social capital.

Table 2: Reuter and MacCoun's drug market conceptualization

<table>
<tr><td></td><td></td><td colspan="2">Customers</td></tr>
<tr><td></td><td></td><td>Mostly residents</td><td>Mostly outsiders</td></tr>
<tr><td rowspan="2">Dealers</td><td>Mostly residents</td><td>Local market</td><td>Export market</td></tr>
<tr><td>Mostly outsiders</td><td>Import market</td><td>Public market</td></tr>
</table>

Source: Reuter & MacCoun (1992).

Summary

One of the more potent harms of drug markets may not be the sale and ingestion of illegal substances but the violence that tends to occur within and near drug market areas. Outdoor drug sales appear to correlate with violent offending such as aggravated assaults (Martínez, et al., 2008), robberies (Berg & Rengifo, 2009; Martínez, et al., 2008), and homicides (Ousey & Lee, 2002). Furthermore, the relationship between drug crime and violence persists, even after controlling for social correlates (Berg & Rengifo, 2009), suggesting that our current understanding of this social problem is incomplete. Environmental criminology has begun to address this void in considering why drug offenders prefer certain locations over others (Rengert, 1996b). In spite of the above empirical research and some theoretical propositions, little knowledge exists qualifying a connection between the travel distances of drug offenders and within-market violence.

Crime pattern theory (Brantingham & Brantingham, 1993) as well as routine activity theory (Cohen & Felson, 1979) have been overwhelmingly responsible for steering research on the journey to crime. Little research however, has addressed the travel distances of drug offenders (Johnson, et al., under review; Pettiway, 1995), and no research to date has empirically investigated whether travel distance correlates with community violence. Part of this problem stems from confusion over how to appropriately operationalize drug markets (Ritter, 2006). In lieu of spatially outlining areas of high drug activity, much research has aggregated counts of police drug crime data to census features, leading one to believe that entire block groups and tracts have the ability to take on a drug market characterization (McCord & Ratcliffe, 2007; Robinson, 2008). Furthermore, little research has critically examined correlates of drug offender travel distance. Two exceptions include Johnson et al. (under review) and Pettiway (1995). It is not yet clear how sociodemographic variables of individuals influence their decisions to travel shorter or longer distances, nor is it understood how market level demographics and contexts influence changes in individual travel distances. Moreover, no one has considered how the aggregate travel distance of buyers and sellers uniquely impacts within-drug market violence, controlling for the contextual effects of market areas. These voids contribute to current misunderstandings of how interactions of market participants from varying travel distances may impact within-drug market violence (Reuter & MacCoun, 1992).

This dissertation addresses the first void by using crime incident data and hierarchical clustering to spatially define drug markets by the presence of statistically significant clusters of drug activity. Prior research has demonstrated that drug crime is not randomly distributed across space (Hunt, et al., 2008; Lum, 2008)—the same is expected to be found from this study.

Second, in line with past research on the journey to crime, it is expected that this dissertation will confirm short journeys to drug offending. This dissertation will contribute to the existing understanding of journeys to drug markets by using hierarchical linear modeling (HLM) to distinguish the amount of variation in travel distance accounted for by individual behavior versus that accounted for by drug market characteristics.

In addressing the third void (of a lack of drug offender journeys to crime research), this dissertation employs separate Poisson hierarchical linear models of buyers and sellers to examine the time-varying contextual effects of travel features on drug market violence. In other words, this research examines how changes in the distribution of travel distances of buyers and sellers over time affect changes in within-drug market violence. Theoretical arguments suggest that there will be a positive relationship between the aggregate travel distances of buyers and sellers, and violence (Reuter, 2000).

Finally, this dissertation presents the first test of Reuter and MacCoun's hypothesis on how the interactions of buyers and sellers from varying distances impact violence. Most importantly, it considers whether Reuter and MacCoun's (1992) typological characterization of markets based on buyer and seller distance patterns relative to one another is an explanation of within-drug market violence. Time-varying Poisson hierarchical models are used to compare the relative effects of covariates resembling the typology. Relatively speaking, it is expected that the covariate that is a proxy indicator for import markets will predict the largest increase in violent crime counts, followed by public, export, and local markets (Reuter, 2000).

CHAPTER 3:

DELINEATING DRUG MARKETS

Introduction

In this chapter, the dissertation spatially bounds drug markets based on of statistically significant spatial concentrations of drug sale incidents. Drug markets—as distinct from single drug sale locations—are areas where a drug user could expect to find more than one drug sale operation and could hope to encounter a drug seller within a general area.

The current chapter begins the systematic analysis of the relationship between travel distance to drug markets and violent crime by operationalizing and defining the spatial limits of drug markets in the city of Philadelphia. It provides an alternative method to create distinct boundaries of drug markets by identifying areal concentrations of criminal incidents using the nearest neighbor hierarchical clustering technique. As illustrated in the literature review, much past research has merely aggregated totals of drug sales incidents to block group areas. That approach ignores the spatial concentration of incidents and may exaggerate the nature of the problem. Indeed, recent research has suggested that using more refined, spatially sensitive measures of drug markets may better our understanding of the extent to which they coexist in violent areas (Lum, 2011).

Data

Drug crime data were sourced from the Philadelphia Police Department's Incident Transmittal System (ITS) in March of 2011, covering the five-year period

(January 1, 2006 to December 31, 2010). This database maintains a list of founded events of which a police officer deemed factual or 'founded'. This can occur in two ways. First, concerned citizens may place calls to 911, which are recorded by the Computer-Aided Dispatch (CAD) system. A vast majority of calls may result in no action on behalf of the police department. Calls that merit police attention result in an officer being dispatched to the reported location. Upon arrival at the reported location, an officer will assess the scene and report that the call was 'founded' (indicating that there was an actual event meriting police attention at the location) or 'unfounded' (indicating that the officer was unable to identify any suspicious activity). Founded events are recorded in the Incident Transmittal System and assigned a UCR code describing the most serious criminal activity. Second, police officers may encounter a situation that merits a police response. Upon discovering the activity the responding officer will notify dispatch (CAD) of the situation. Depending on the seriousness of the event and response by the officer, the incident will be assigned a corresponding UCR code. For example, an officer may receive notice of a possible drug sale from dispatch. After arriving on the scene of the advertised drug sale, the officer may observe a person advertising the sale of heroin under a street name. After investigating the matter more closely the officer may discover heroin in someone's possession. As a result, the officer will notify CAD of the findings and the incident will be assigned the UCR code of 1805—the code for the sale of heroin.

Incident data derived from the Incident Transmittal System detail the date of the incident, UCR code, and X/Y coordinates of the incident location and district control (DC) number. UCR codes were used to extract drug incidents from the ITS for the sale of any of the following: opium, marijuana, synthetic/manufactured narcotics, dangerous non-narcotic drugs, powder cocaine, and crack cocaine. A total of 18,299 drug sale incidents occurred from 2006 to 2010 in the city of Philadelphia. See Table 3 for a list of drug UCR codes.

Table 3: Drug UCR codes used in analyses

UCR Code	Crime description
1800 series	**Narcotics/drug law violations**
	Seller of:
1801	Opium and its derivatives (Morphine, Codeine)
1802	Marijuana
1803	Synthetic/manufactured narcotics (Demerol, Methadone)
1804	Dangerous non-narcotics (Barbiturates, Benzedrine)
1805	Heroin
1806	Cocaine (Powder)
1807	Cocaine (Crack)

Source: Philadelphia Police Department (2001).

Methodology

Drug markets are distinguished from other areas by statistically significant spatial concentrations of drug sale incidents. Arrests for drug selling are more likely than those for drug possession to take place within or near the drug market, since outdoor drug sellers are territorial in nature (St. Jean, 2007). A drug possession incident could simply indicate that an arrestee possessed drugs at that location, but not necessarily that the arrestee purchased drugs in the same location. It is possible that an officer didn't witness the arrestee buy drugs, but that after a search due to some other suspicious activity the officer found drugs on the arrestee's person. Such an arrest could happen at or near a drug market area, but it could also happen anywhere else, making it theoretically difficult to link their arrest with that of a drug market. In a similar vein, arrests for the manufacture, delivery, or possession with the intent to deliver drugs are likely to resemble social network markets where buyers place orders over the phone and meet sellers at predetermined locations, rather than more fixed site stable areas of drug activity.

Conceptualization of drug markets as significant clusters of sale incidents requires a binary spatial classification technique. Smoothing algorithms such as kernel density estimation are not appropriate because they fail to outline distinct boundaries of drug markets, but instead use a continuum of values classified into arbitrary groups (Levine, 2004).

Point location techniques such as the mode and fuzzy mode of the CrimeStat software package also fail to meet the needs of this research because they merely total the number of events taking place at or within a certain distance of user-determined features such as transit nodes or other point locations. Those techniques would be appropriate for assessing the count of robberies in and around a specified set of alcohol-serving establishments but not for determining statistically significant concentrations of arrests (Levine, 2004).

Partitioning cluster tools typically assign all events to a user-defined number of clusters, with each point belonging to one cluster exclusively (Levine, 2004). Such techniques are likely to identify multiple clusters; however, that are not necessarily clusters. This is because these techniques assign *every* point to a cluster. Furthermore, they require *a priori,* a user-defined estimate of the number of likely clusters. This is inappropriate for the current research which seeks to discriminate significant clusters of drug arrests from those arrests dispersed across space.

According to Grubesic and Murray (2001) “Broadly defined, cluster analysis is a method of classification that places objects in groups based on the characteristics they possess” (p. 5). Hierarchical clustering techniques have existed for many decades (Johnson, 1967; Sneath, 1957; Ward, 1963) in both parametric and non-parametric forms (D'Andrade, 1978). Hierarchical clustering routines begin by calculating some measure of dissimilarity (commonly distance) between each point and all other points in a population (Bailey & Gatrell, 1995). An average of the nearest distance among all points is typically computed and used as a threshold for grouping points across space (random nearest neighbor distance). Two or more points whose separation distance is less than the nearest neighbor distance[7] are then grouped into a series of first-order clusters. Second-order clusters are created by repeating the same process on the primary clusters already generated. According to Levine (2004), second-order clusters are grouped into larger ones, and this process is repeated until no additional clusters can be identified. Visually, hierarchical clustering resembles an inverted tree diagram (see Figure 2), yet it is important to note that not all points are grouped into a cluster (Levine, 2004).

[7] Other measurements can be used to define the threshold such as the minimum distance and maximum distance (D'Andrade, 1978).

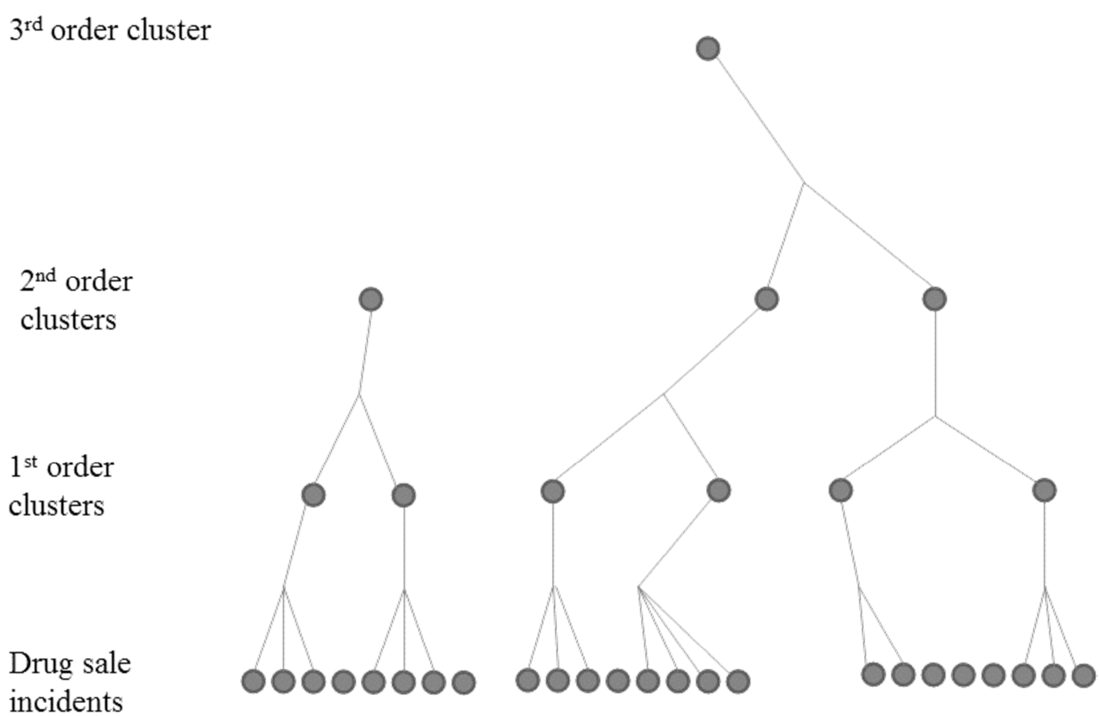

Figure 2: Hierarchical clustering technique (adapted from Levine, 2004, p. 6.3)

Nearest neighbor hierarchical clustering (Nnh) is a technique within the CrimeStat package which outlines clusters of point data (Levine, 2004). Similar to the general description of hierarchical clustering above, CrimeStat's Nnh technique uses a threshold distance to group points into a cluster. Two main criteria guide the clustering process. The first criterion is the selection of a threshold distance. Nnh allows users to select their own fixed distance threshold, or to use the random nearest neighbor distance for first-order clusters. The random nearest neighbor distance is defined as:

$$d(ran) = 0.5\sqrt{\left(\frac{A}{N}\right)}$$

where *A* is the size of the study area (defined by the user) and *N* the number of spatial events (Levine, 2004).

The threshold distance is determined by selecting the appropriate one tailed confidence interval around the random nearest neighbor distance. Therefore, the confidence interval for the random nearest neighbor distance equals the random nearest neighbor distance plus or minus the standard error of the mean random nearest neighbor distance:

$$0.5\sqrt{\left(\frac{A}{N}\right)} \pm t\left(\frac{0.26136}{\sqrt{\frac{N^2}{A}}}\right)$$

where A is the size of the study area, N is the number of spatial events, *t* is the Student t-value for a given probability level, and 0.26136 is a constant. Here, the confidence interval is used to determine the probability that the distance between any pair of events would be less than the random nearest neighbor distance (if we assumed the data are randomly distributed across space). In other words, if the data are *randomly distributed* and said user selected significance at p <.05 then about 5% of the pairs of events could be expected to be closer than the random nearest neighbor distance (Levine, 2004).

In order for the program to employ the random nearest neighbor distance option, the user must first define the area of the study region. This can occur by way of user input, or by allowing the program to use the default option. In the first scenario, the user enters a value reflecting the area of the study region. In the second scenario, the program identifies the smallest X/Y coordinate crime location and the largest X/Y coordinate place (essentially the lower left and top right extent of the data), which are then used to identify a rectangle enclosing all drug sale incidents across the city of Philadelphia. The area of the rectangle is then used as a proxy of the study area. Theoretically speaking, a smaller area will result in fewer and denser clusters than a larger area. This is merely because as area increases so too does the opportunity for dispersion. After the user details the area, computation of the random nearest neighbor distance is an automated process (Levine, 2004).

The second criterion is the selection of a minimum number of points necessary to create a cluster. This criterion is necessary to reduce the number of very small clusters that would otherwise be created by chance. A large dataset can result in many clusters if the only requirement were that points were within a specified distance of one another. As a result of this criterion as well as the one described above, points will only be clustered if the distance between them is less than the set threshold *and* if the number of points in the cluster is greater than or equal to the minimum set by the user (Levine, 2004).

For the purposes of this research Nnh is used to identify significant clusters of drug activity due to theoretical interests and research testifying to its superiority over other techniques in identifying concentrated clusters (Levine, 2008). A Nnh analysis was run on the drug sale incident data using the following parameters. The land area value used to calculate the random nearest neighbor distance was 135.1 square miles, due to the irregular shape of Philadelphia and the possibly that the minimum bounding rectangle may provide an inaccurate estimate the likelihood of clustering (personal communication with N. Levine, 2012). A 95% confidence interval was used to determine the probability that the distance between any pair of events would be less than the random nearest neighbor distance (assuming the data are randomly distributed across space). Ten (10) was chosen as the minimum number of points necessary to create a cluster (the default option). Supplemental analyses exploring the sensitivity of that parameter are explored later in this chapter.

Results

Descriptives

Nnh analysis revealed 329 first-order, 34 second-order, and 2 third-order clusters, shown in Figure 3. For purposes of clarity, the map on the left side of the figure shows the first- and third-order clusters. First-order clusters appear as small specks or dots on the map. Third-order clusters appear to resemble large drug market regions. They are located close to one another in North Philadelphia, in an area historically known as 'The Badlands'. The map on the right side of Figure 3 displays the locations of the 34 second-order clusters revealed by the Nnh analysis which are concentrated throughout North and West Philadelphia.

Figure 3: 1st and 3rd order clusters of drug sale incidents (left), 2nd order clusters (right)

Table 4 provides descriptive statistics for each of the cluster-orders produced from the hierarchical clustering process. Three-hundred twenty-nine first-order clusters were estimated using the Nnh technique. First-order clusters possess a median area of almost 5,000 square feet, indicating that these clusters are generally very small and cover an area resembling the size of a street intersection. The minimum area value of zero is the result of some first-order clusters resembling "problem" addresses that have had multiple calls for service for drug activity. For example, over the five-year study period, 61 separate incidents for the sale of illegal drugs occurred near the corner of N. 61st Street and W. Thompson Street in West Philadelphia.

There were a number of operational difficulties with both first- and second-order spatial clusters. First-order clusters, when examined for a city such as Philadelphia, identify a large number of very small areas often concentrated around street intersections. Even though the clusters each contained points that were within the random nearest neighbor distance, and constituted sufficient offenses to overcome the minimum number of points threshold, these first-order areas were deemed to be too small for use, as they were more representative of drug selling corners rather than larger areas of agglomeration drug markets applicable to this research. A second-order spatial unit was therefore considered.

Table 4: Descriptive statistics of hierarchical clusters (square miles)

Clusters	n	Median area	Mean area	St. Dev. area	Minimum	Maximum
1st order	329	1.71E-04	3.67E-04	4.52E-04	0.00E+00	2.28E-03
2nd order	34	0.03	0.04	0.03	1.19E-03	0.12
Merged	34	0.03	0.04	0.03	1.42E-03	0.12
Buffer	34	0.07	0.08	0.03	0.02	0.16
3rd order	2	0.48	0.48	0.20	0.34	0.63

A total of 34 second-order clusters were produced by the Nnh analysis, and are substantially larger than those within the first-order. Second-order clusters have a median area of slightly over 0.03 square miles, or about 5 ½ city blocks. Second-order clusters collated various first-order clusters into more cohesive units, but did so based on the centroid of the first-order clusters. Table 5 displays descriptives of first-order clusters, controlling for whether or not they were captured by a larger second-order cluster. Of the 329 original first-order clusters, 224 or 68% are also within the second-order hierarchy. The remaining 105 first-order clusters fell outside of the larger second-order units. A *t*-test[8] was used to compare the average area of first-order clusters captured by second-order units (M = 4.07E-04, St. Dev. = 4.73E-04) to those falling outside of second-order clusters (M = 2.83E-04, SD = 3.94E-04). Results indicated that first-order clusters captured by second-order clusters are significantly larger in terms of area than clusters not captured by the second-order, $t(327) = 2.33$, $p < .05$.

[8] Independent-samples *t*-test, equal variances assumed.

Table 5: 1st order clusters captured by 2nd order clusters (square miles)

Clusters	n	Median Area	Mean area	St. Dev. area	Minimum	Maximum
1st order	329	6.13E-12	1.32E-11	1.62E-11	0.00E+00	8.18E-11
1st order in 2nd order	224	2.59E-04	4.07E-04	4.73E-04	0.00E+00	2.28E-03
1st order lost	105	5.71E-05	2.83E-04	3.94E-04	0.00E+00	1.77E-03

Depending on the orientation of the first- and second-order spatial units, a considerable number of crime events within first-order clusters were excluded from second-order clusters, even when they were members of a first-order cluster that was part of the second ordering. This problem is demonstrated in Figure 4, where (a) shows a pattern of crime events as grey crosses, amongst which are a number of first-order cluster areas, indicated by black outlined areas. The grey area in (b) shows the second-order hierarchical spatial relationship between a number of the first-order clusters, based on the centroid of the first-order areas. The hollow arrows indicate a couple of areas that were first-order spatial clusters but were too remote from other areas to be included in a second-order cluster. These isolated first-order clusters were not considered further. The black arrows indicate two problem areas, from a drug market perspective. These are crime event clusters that were included in first-order clusters and, although part of that first-order cluster was involved in a second-order cluster, part of it was excluded. This happened because centroids of first-order clusters are used by the Nnh analysis to construct the shape of the second-order clusters. Because of this problem, some events can be inadvertently excluded.

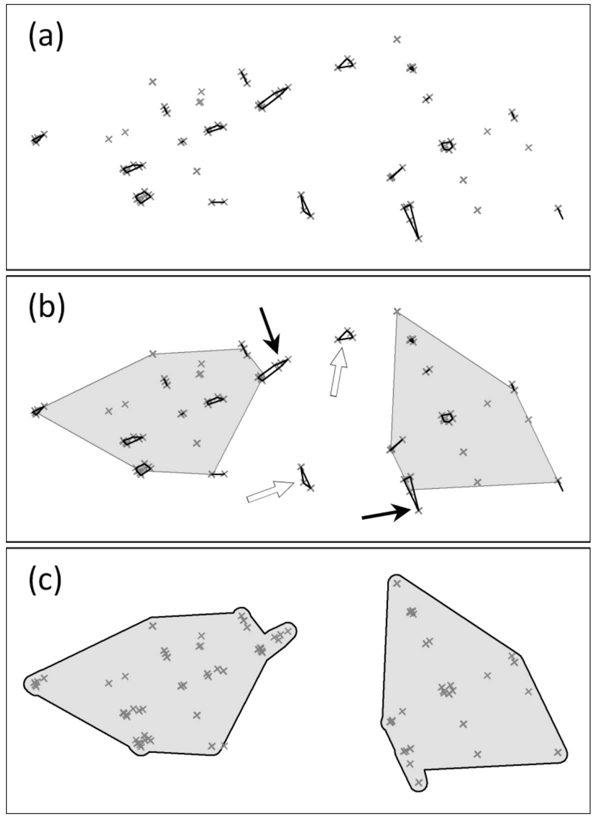

Figure 4: Modification of the nearest neighbor hierarchical clustering process

The solution was to spatially merge the first- and second-order clusters so that points were contained within an entire first-order cluster were not lost when the second-order hierarchy was applied. This is demonstrated in part (c) of Figure 4. Once related points were identified, a convex hull approach was applied to define a polygon that contained all related points within a minimal shape (Chrisman, 2002). In part (c) the final combined first- and second-order polygon areas have had a small buffer applied for purposes of visual clarity.

Descriptive statistics of merged first- and second-order clusters are shown in Table 4, and indicate that the median size of the merged clusters is not substantially different from the second-order clusters. This is because the first-order clusters generally covered very small areas and contributed very little area to the second-order clusters, once they were merged. Conversely, the two third-order clusters appear to denote drug regions of the city. The smaller cluster has an area of .34 mi^2, and the larger is .63 mi^2.

Third-order clusters were deemed too large for the purpose of this research and will be excluded from further analyses. The focus of this research is to identify problem drug market areas that are amenable to local problem-oriented policing approaches. As such, it is necessary to identify a unit of analysis that is large enough and demonstrated enough problems over time to attract police attention at the public service area level, not the district or senior management levels (Johnson & Ratcliffe, in press). Third-order clusters may demand the attention of senior management. Furthermore, they are large (spatially) and thus more likely to be internally heterogeneous on demographic, social, and economic factors. This suggests that potential operational intervention strategies for second-order cluster areas are likely very different from third-order cluster areas.

Rigidity of convex hulls

Three issues arise from using Nnh to identify spatial clustering. The first problem is the concern about the rigid nature of the convex hull clusters. According to Levine (2004) the advantage of using convex hulls is that they reflect an outline of clustered points, but the disadvantage is that they may exclude areas that should be included in the market. Furthermore, there could be incidents related to the drug market but outside of its rigid boundaries. This problem was addressed in this dissertation by creating a buffer around each cluster to capture drug and violent incidents possibly associated with the drug market but originally excluded by the convex hull. In selecting the proper buffer size the user must balance the need to include points within a theoretically relevant distance of the clusters while not making buffer areas so large that they overlap one another. This is especially important in the North Philadelphia – Badlands area where some of the clusters are within one city block of another (see Figure 3). Unfortunately, little empirical guidance is available on the selection of buffer sizes.

According to Guerette (2009) three things should be considered when selecting buffer sizes. First, he argues that there must be some logical expectation for displacement to occur. Displacement is immaterial to this study because there is no treatment being applied in the study. It is possible, however, that incidents that occurred outside but near drug markets are associated with those drug markets. For example, an officer may have witnessed a drug transaction occur within a drug market area yet instead of making an arrest there, may have allowed a buyer to walk away from the market to an area where an arrest would draw less attention. Second, researchers must be cautious in the selection of buffer size. Large buffers may encompass too much data and dilute statistical relationships. Conversely, small buffers may fail to capture incidents theoretically associated with drug market areas. Third, buffers should be free of contamination effects. In terms of spatial research, this refers to overlap between buffers. Overlap can result in the double-counting of crime incidents within drug market areas. Additional research by Ratcliffe and Breen (2011) has suggested the use of buffers that consider the urban landscape. Real and perceived edges structure decisions on criminal offense locations (Rengert, Lockwood, & McCord, 2012). Thus certain edges such as abrupt changes in land use may serve as barriers to displacement in areas contiguous with target areas. The displacement may, in fact, occur in an area that is *not* contiguous such as a related land use nearby the target area, but not adjacent. Once again, these issues are noteworthy but not of issue here since this research does not estimate the impact of a police intervention.

The median length of a street segment in Philadelphia is roughly 200 feet. Using a buffer of the same size would theoretically mean that any incident within 200 feet of a drug market's boundary is attributable to the dynamics of that drug market. Similar to Figure 4c, a 200-foot buffer was applied to the merged clusters to capture additional incidents that may be outside the boundaries of the drug market but nonetheless related. The left half of Figure 5 displays a map of Philadelphia, with the drug markets including a 200-foot buffer. The dashed rectangle indicates the region displayed on right half of Figure 5. The shaded polygons indicate areas where two markets overlapped one another. Statistically speaking, overlapping areas violate the assumption of independent observations. In line with research by Haberman, Groff, and Taylor (in press) this problem was resolved by measuring the distance from the centroid of each overlapping area to that of its respective drug markets. Each overlapping area was then merged with its closest drug market.

Figure 5: Drug markets with 200 foot buffer applied

Monte carlo simulation

The second problem with the Nnh analysis concerns how to determine statistical significance of the clusters (Levine, 2004). The test to determine whether two points are clustered by chance is the confidence interval around the random nearest neighbor distance. If the probability level is set to .05 then one could expect that 5% of all point pairs are grouped by chance, assuming a random distribution. However, Nnh groups more than just two points within a cluster, depending on the minimum number of points set by the user. A Monte Carlo simulation can address this problem by constructing confidence intervals based on the first-order clusters. It is essentially a test of the null hypothesis that the data are *not* spatially clustered. This occurs by randomly assigning the same number of cases to a rectangle containing the same area as the study region. For each simulation (the total number of simulations is determined by the user) the program calculates the number of clusters created and categorizes them according to percentiles of the number of clusters revealed from each Monte Carlo simulation. Additionally, the number of points, density, and area are calculated for each cluster.

A Monte Carlo simulation was run on the data, using 1,000 iterations. In other words, the 18,299 drug sale incidents were randomly thrown on a plane with an area matching the square footage of Philadelphia, 1,000 times. Across all iterations of spatial randomization, zero clusters were produced. This indicates that it is highly unlikely that any of the first-order clusters were produced by chance, and therefore the data are significantly clustered compared to what would be expected if they were randomly distributed.

Sensitivity analysis

The third issue is that the selection of a minimum number of points does render Nnh slightly arbitrary (Grubesic & Murray, 2001). Research has yet to empirically guide its selection. Personal communication with N. Levine (2010) confirms that the minimum point selection is arbitrary; however, the purpose of the option is to minimize the number of extremely small clusters. In this research, a minimum of 10 points were selected to create a cluster, which is the default option.

Table 6: Sensitivity analysis

Min. # of points	Observed 1st-order clusters	% change	Expected clusters obtained by chance (95th percentile)
8	420		1
9	375	-10.71	1
10	329	-12.27	0
11	307	-6.69	0
12	266	-13.36	0

To determine the sensitivity of this option, the analysis was re-run using 8, 9, 11, and 12 points as the minimum. There appears to be an inverse relationship between the minimum number of points selected and the number of first-order clusters produced (see Table 6), which substantiates communication with N. Levine (2010). Increasing the minimum number of points necessary from 9 to 10, decreases the number of clusters produced by 12%. Using 11 points instead of 10 points decreases the number of clusters by an additional 7%. Monte Carlo simulations were run for each additional analysis using 1,000 iterations to determine the number of clusters that would be obtained by chance, assuming a random spatial distribution. Results indicate that when setting the threshold to eight or nine points, using 18,299 incidents it is possible that one cluster (or in this case drug market) is a statistical artifact. Selecting any number of points greater than nine reduces the chance of statistically artificial clusters to essentially zero. This suggests that clusters revealed by setting the minimum number of points to ten are non-random clusters of drug sales activity. Therefore, the appropriate minimum number of points selected for these data is any option of at least ten points, noting that there is an inverse relationship between the minimum number of points and the number of first-order clusters that will be identified.

Discussion

The current chapter has proposed an alternative method to spatially operationalize drug markets. Much of the past research on drug markets has accomplished this by aggregating counts of police drug sales data to census defined geographies. Although this allows researchers to conveniently append census data, such an operationalization has the potential to be over-inclusive and runs the risk of labeling entire census block groups or tracts as drug markets when the reality is quite different. This becomes apparent when we consider research indicating that neighborhood drug problems can stem from places as geographically small as one address (Mazerolle, et al., 2004). Using official drug crime data from the Philadelphia Police Department, this chapter has shown that the nearest neighbor hierarchical clustering technique addresses this limitation by identifying significant clusters of drug incidents at multiple geographic levels ranging from street intersections to areas of over half of a square mile. Although this example of the nearest neighbor hierarchical clustering technique used drug sales incident data, the general cluster identification process can be applied to other crime categories, such as violence.

Perhaps the most detrimental aspect of urban drug markets is the violence by which they are often characterized (Berg & Rengifo, 2009; Martínez, et al., 2008; Ousey & Lee, 2002). Although studies such as these contribute to our understanding of violence, they are limited in terms of how they operationalize and conceptualize drug markets. A positive relationship between neighborhood census tract drug arrest rates and violence is operationally and conceptually different from empirically derived statistically significant clusters of drug sales arrests and the violence that occurs within. The former examines community correlation between drug arrest rates and violence while the latter focuses on the significance of the most problematic drug crime areas (hot spots) and how they engender violence. In sum, operational and conceptual processes are subject to the unit of analysis under study (Taylor, 2010a).

Findings here also provide an impetus to revisit existing theory on drug markets. For example, the systemic model of violence argues that the violent nature of drug markets is normative to the nature by which illicit drug transactions take place. In other words, because illicit drug markets operate in a world unregulated by legal standards, disputants within drug markets are unable to seek the help of the criminal justice system to settle conflicts. As a result, market participants use alternative measures to redress their grievances, and at times the measure of choice is violence (Blumstein, 1995; Goldstein, 1985; Messner, et al., 2007; Mieczkowski, 1992). The hierarchical clustering technique would aid in not only determining more realistic drug market areas, but also in examining the amount and kinds of violence that take place within.

Although clustering techniques such as the one described here are fundamentally descriptive in nature and often the starting point for an analysis rather than an end point, hierarchical clustering could provide crime analysts with a more accurate method for targeting police resources across multiple levels of police organization. For example, Figure 3 suggests that first-order clusters which tend to outline street intersections or problem addresses may be of interest to beat officers who routinely patrol assigned areas and need to be aware of potential threats. District commanders may see more value in larger, second-order clusters that outline larger areas of drug activity as useful for the assignment of additional officers, or for planning neighborhood level community oriented policing or situational crime prevention efforts. Such information could aid in the planning of police crackdowns and the targeting of specific drug sellers or selling organizations that may be the cause of violence in the community. These areas are also more conducive to community organization. Third-order clusters may be of interest to police executives and federal agencies that plan for the assignment of personnel at scales larger than local police districts. Although targeted police efforts to hotspots may cause some displacement, interdiction of the most spatially advantageous sites may displace sellers to less advantageous locations in turn making the market less profitable (Robinson & Rengert, 2006).

The technique shown here therefore has the capacity to indicate at least three levels of drug market organization that roughly conform to commonly used drug market terminology;

- Level one spatial clusters equate to *drug corners* (such as around an intersection)
- Level two spatial clusters equate to *drug markets* (groups of blocks with drug problems)

- Level three spatial clusters equate to *drug regions* (such as the Philadelphia Badlands)

These spatial units have operational benefits to crime science and crime prevention. The first two spatial clusters operate at scales that are amenable to local policing and problem-solving approaches, while the third scale indicates a region or area than may need a broader investment to combat the drug problem.

It is recognized that although this research is an attempt to bring a geographically data based approach to the spatial identification of urban illicit drug markets, there still remains the issue of the arbitrary minimum number of points required to form a level one cluster. It is hoped that additional research will identify some guidelines to inform future decisions. In the meantime, one recommends that analysts using this approach clearly publish this chosen number in any maps and publications.

A final theoretical note deserves comment. It is possible that the drug markets constructed from the nearest neighbor hierarchical clustering technique are not real, but abstractions of reality. Recent work by Taylor (2010) argues that there are several inconsistencies that hot spot policing researchers must address before hot spot policing can advance to a national policy. Among these concerns includes the idea that hotspots are real places, instead of characteristics of a place or group of places. Additionally, there is no set of policies that serve to describe what hot spot policing entails, in turn making it difficult to prioritize this approach over many others. Although it is not in the theoretical interest of this work to address the nuances of hot spot policing at the national level, Taylor's point does bring into question the construct validity of hot spots techniques.

Analytically and methodologically this work has taken steps to address some of these concerns, and communication with the Philadelphia Police Department during the summer of 2009 has anecdotally confirmed that many of the drug markets outlined in this work are areas of high drug activity.

CHAPTER 4:

JOURNEYS TO BUY AND SELL ILLEGAL DRUGS

Introduction

With the exception of research by Johnson, Taylor, and Ratcliffe (under review), very little research has systematically analyzed travel distance for drug buyers *and* controlled for market-level and individual-level influences on those travel distances. Although there is some descriptive research on how far individuals travel to purchase illegal drugs, what is still unknown is whether there is variation in buyer and seller travel distances across different drug markets. Considering that literature on drug offender travel distance appears to be in its infancy, the current work is largely exploratory. Of particular interest here is whether travel distance in some way correlates with drug market violence. The current chapter provides a bridge between Chapter 3 which spatially identifies drug markets, and Chapter 5 which considers potential statistical correlations between distance traveled to markets and violence.

In addition to the above gaps in drug offender journey to crime research, it is unknown whether the same variables that explain travel distance to other crime types also apply to drug offending. Certainly official data limit the variables under consideration; it is possible however, that certain processes will be revealed that will further our understanding of the travel decisions of buyers and of sellers. In the pages that follow, individual level factors shaping the travel decision, including drug type, and drug market characteristics are both explored to predict travel distances of buyers and drug sellers.

Demographic and structural implications are noted. In sum, three questions will be answered in this chapter:

1. How far do drug offenders travel to arrest locations? (Buyers and sellers are considered separately for this and other questions.)
2. What is the role of individual drug offender and market level demographics on individual travel distance?
3. How does drug choice (to buy or sell) influence the travel decision?

Data

In addition to the drug sale incident data described in Chapter 3, drug buying incidents were extracted from the Philadelphia Police Department's Incident Transmittal System. DC numbers are unique identifiers attached to incidents recorded in the Incident Transmittal System. Regardless of the number of co-offenders involved in a criminal incident, the Incident Transmittal System only records one incident and attaches only one corresponding DC number. DC numbers are recorded in the YYYYDDNNNNNN format, where YYYY indicates the year of the incident, DD is the district within which it took place, and NNNNNN is the numerical position of the incident within the host police district for any given year. DC numbers are critical for linking incidents to arrested individuals because they are attributed not only to incidents but to individuals alleged to be responsible for those incidents. Therefore, in the case of co-offending, multiple arrestees can have the same DC number. Remaining arrestee variables are maintained in a separate dataset, which is described below.

The second dataset is derived from the Philadelphia Preliminary Arraignment System (PARS). PARS is an electronic database shared among the Philadelphia Police Department, Philadelphia County District Attorney's Charging Unit, Philadelphia Municipal Court, and the Pretrial Services Agency to process arrestee movements through the local criminal justice system (General Accounting Office, 2001). Of particular interest here are the demographic variables recorded for each arrestee. In addition to the DC numbers described above, PARS data include the following information on arrestees: date of arrest, date of birth, race, gender, Latino status and home address.

Methodology

Recall that the theoretical interest of this dissertation is to understand how drug buyer and seller distance distributions collectively shape market violence. In this part of the dissertation however, determinants of drug buyer and drug seller travel distance are separately examined. This approach is necessary to control for the possibility different causal relationships explaining drug buyer versus drug seller travel distance. In turn, it is necessary to not only to understand where they offend (detailed in the Incident Transmittal System), but also their demographic characteristics and—most importantly—the locations from which their journeys to drug crime begin. Microsoft Access was used to link drug related incidents maintained within the Incident Transmittal System to arrestees within PARS using DC numbers. This link allows for the creation of a single file detailing incident characteristics and corresponding arrestee characteristics. The Philadelphia Police Department conducted 85,064 *arrests* for the sale or purchase of illicit drugs for 58,932 *incidents* that occurred from 2006 to 2010. This suggests that not only was co-offending taking place, but also that it is highly likely that some individuals were arrested more than once. Including multiple arrests of the same individual would force this research to consider the possibility of individuals altering their travel behavior over time, due perhaps in part to subsequent attempts to avoid further detection by criminal justice personnel.[9] Although an interesting topic in its own right, and one that may be considered in future work, this is not a key interest of this dissertation. Admittedly, excluding subsequent arrests within the five-year study period does not preclude the possibility that an individual was arrested prior to 2006 (or after 2010), and that an earlier interaction with the criminal justice system affected the features of the arrest within the study period. Excluding subsequent arrests within the study period does mean however, that each arrest constitutes a unique travel observation for each individual. Limiting the data to each individual's first arrest results in 59,178 cases (or trips) for the sale or purchase of illicit drugs.

Unlike the locations of criminal incidents, the home locations of drug arrestees are not presented in the form of X/Y coordinates, but in street address format. Street addresses were geocoded[10] to provide X/Y coordinate pairs describing the home location, and data were appropriately projected (NAD 1983 StatePlane Pennsylvania South FIPS 3702) to preserve distance in terms of feet. Street addresses were then deleted as such information is immaterial to the analyses presented here. The geocoding process yielded a 94% hit rate with 55,660 addresses located.

[9] This point is illustrated by Townsley and Sidebottom (2010) who found evidence of a distance-decay curve when ignoring the nesting of arrests within individuals. However, when reviewing the standardized skewness scores of offenders with 10 or more burglary trips they found that 60% of offenders demonstrated a negative skew.
[10] Geocoding is "[t]he process of creating map features from addresses, place-names, or similar information …" (Ormsby, Napoleon, Burke, Groessl, & Feaster, 2004, p. 429).

This dissertation also limits analysis to trips that originated within the Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metropolitan Statistical Area.[11] Figure 6 displays a map of the region, in which 55,532 trips originated and ended.

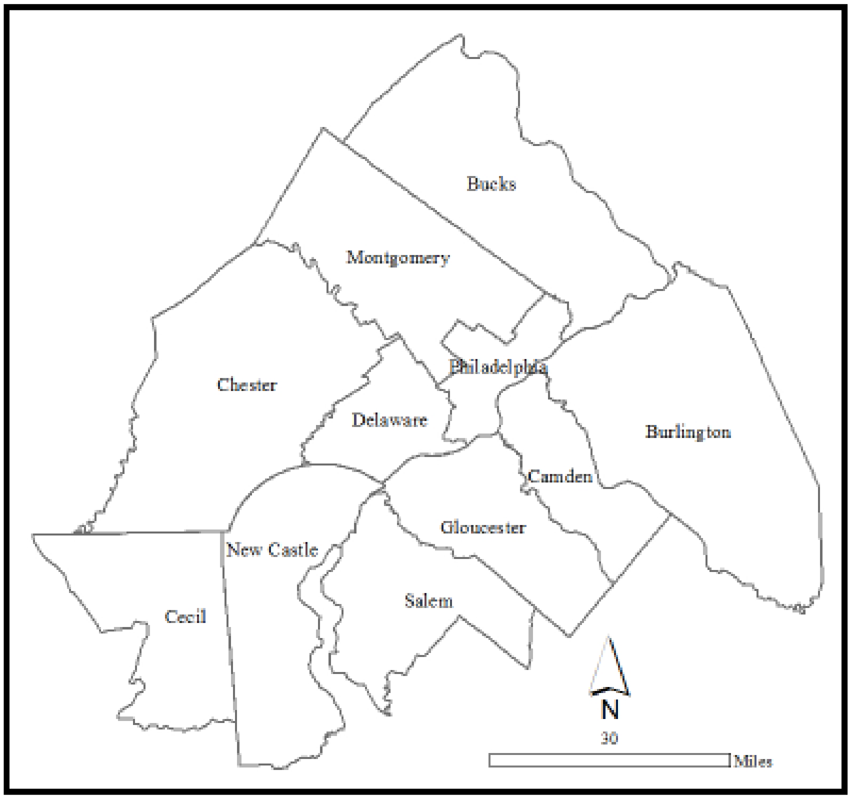

Figure 6: Counties in the Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metropolitan Statistical Area

Variables

Outcome

The outcome of interest for this part of the study is distance traveled. Distance from the offender's residence to the arrest location was calculated by determining the

[11] "Metropolitan Statistical Areas have at least one urbanized area of 50,000 or more population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties" (Orszag, 2009, p. 8).

street network difference in miles from the X/Y coordinate of the home to that of the arrest location.

Theoretically, this indicator assumes that offenders make direct trips from the home to the incident location. This may be unlikely. For example, Rengert et al. (2000) found that crime clusters around drug treatment centers. This suggests the treatment centers may serve as nodes, crime generators, and origins of crime journeys if a potential offender leaves the center and travels to commit crime in the surrounding area. Assuming that offenders wake in the morning at home and perhaps conduct a host of routine activities *prior* to arriving at their incident locations, it may be optimal for researchers to use offenders' last known locations prior to traveling to incident locations. Such an analysis will have to wait for qualitative research as police arrest and incident data are unlikely to have that information. Conversely, research has shown that the home is a major node in the lives of law-abiding citizens and criminal offenders (Brantingham & Brantingham, 1993; Rengert, 2004), and the home appears to be the most common point of origin used in journey to crime research (Capone & Nichols, 1976; Pyle, 1976; Snook, 2004). Thus, while recognizing some of the data limitations of using offender residences as trip origins, the assumption does have some support from crime pattern theory and, it allows researchers to draw conclusions about the extent of crime clustering near the homes of offenders.

An additional concern of journey to crime research is how distance is calculated. Although street network measurement would provide the most accurate measurement of distance by considering the shortest street route from home to the arrest location, it assumes an offender is knowledgeable of the shortest route and actually used it (Groff &

McEwen, 2005). Euclidean measurement considers the straight line distance from point to point; however, it assumes an unrealistic travel pattern and tends to underestimate distances by about 20% (Chainey & Ratcliffe, 2005). Research has shown that Manhattan distance measurement most closely approximates street network measurement (Chainey & Ratcliffe, 2005; Rossmo, 2000) and is appropriate for urban environments such as Philadelphia, PA (Block, et al., 2007). Here the street network distance was used because, given the purposes of this research its limitations are least troublesome. It presents the most realistic route an offender could take between two points using the urban street grid. ArcGIS identified a route for each arrestee as well as travel distance in miles.

Person-specific predictors

UCR codes were used to create *k*-1 dummy variables indicating the purchase/sale of marijuana, powder cocaine, crack cocaine, heroin, or manufactured narcotics (Demerol, methadone). Marijuana was the reference string. To control for compositional effects, dummy predictors were included to indicate gender (1 = female, 0 = male) and race, where African American was included in the reference string and white and Hispanic were captured with separate predictors. Age (centered on the mean age across the sample) was included in the level 1 model.

Market-characteristic predictors

The mean age of offenders within each market controlled for an overall age—drug market violence link. The contextual gender variable captured the proportion of females arrested for drug offenses within each drug market. Additional contextual variables measured the proportion of buyers and sellers within markets arrested for buying or selling marijuana, powder cocaine, crack cocaine, heroin, or manufactured narcotics. Separate predictors were used to model the proportion of whites and Hispanics arrested for drug offenses within each drug market.

Analysis

With individuals nested within markets hierarchical linear models (HLM) were used (Raudenbush & Byrk, 2002). In the current chapter, drug offenders were nested within the drug markets of where they presumably conducted business before being arrested. HLM, separates the ecological effects of place (drug markets) from the effects of offenders, and considers whether the variation in travel distance among individuals is partially attributed to the markets within which they bought or sold drugs. It also allows for determining the effects of offender characteristics on distance while controlling for drug market context.

The first set of models answer the following question: How far do arrestees travel to buy illicit drugs? Person-specific predictors entered in the model include buyer gender, age, race, and ethnicity. Hypotheses are in line with prior research suggesting that, overall, offenders travel short distances to offense locations (Block, et al., 2007; Capone & Nichols, 1976) and that older (Snook, 2004), white (Johnson, et al., under review; Warren, et al., 1998; Wiles & Costello, 2000) males (Groff & McEwen, 2005; Pettiway, 1995) will travel farther than younger minorities and females. The second set of models factor in the influence of drug choice. It is expected that heroin buyers will travel farther than other drug buyers as found in prior research (Forsyth, et al., 1992; Johnson, et al., under review).

Additional models determine if there are market level factors that influence individual level travel decisions. At this stage of the analysis market-characteristic predictors were entered into the model to examine the ecological effects of drug market gender composition, drug type composition, race, ethnicity, and age composition on individual travel distance.

Literature has not provided definitive theory to explain travel patterns of drug sellers. Research has suggested, however, that sellers are willing to travel outside of the neighborhood if substantial profits are to be made (Pattillo, 1998). This may suggest that sellers have search patterns similar to residential burglars and are willing to travel longer distances if anticipating greater rewards. The current chapter, in addition to examining the above issues, also explores differences between drug buyer versus drug seller travel distances and compares determinants of each.

Results

Descriptives

Columns 1 and 2 of Table 7 displays untransformed descriptive statistics of the street network distance outcome variable for buyers and sellers. Drug buyers traveled 3.6 miles on average to arrest locations (St. Dev. = 6.2 miles) while sellers traveled slightly less far with an average distance of 2.8 miles (St. Dev. = 4.9 miles). The median distance score for both groups was roughly similar (1.14 miles for buyers versus 0.99 miles for sellers). The zero mile minimum distance for both groups suggests that some individuals were arrested at their home residences. The maximum travel distance for buyers and sellers whose trip origins began in the Philadelphia metro area was 63 and 66 miles, respectively.

Skewness and kurtosis statistics for both outcome variables as well as visual inspections of histograms (not shown) revealed non-normal distributions. The decision was made to transform both variables using the natural log, useful for shifting positive skews to a more normal distribution. The second half of Table 7 provides results of that transformation. When considering buyers, the natural log transformation reduced the skewness and kurtosis values from 3.36 and 14.64 to -1.03 and 2.2 respectively. For sellers, transforming the distance variable reduced the skewness and kurtosis values from 4.1 and 24.18 to -.98 and 1.87, respectively.

Further analytical preparation approaches were considered. A boxplot analysis of the natural log transformed variables revealed that 122 extreme outliers[12] exist with values less than or equal to -5.2 (about .0055 miles) for buyers, and 318 cases with values less than or equal to -5.1 (about .0061 miles) for sellers. Excluding outliers for both outcomes moved skewness and kurtosis values within the -1 to 1 range. The weakness of this approach is that it excludes a number of cases. An alternative that does not require the user to drop cases is known as Winsorizing. Winsorizing replaces each extreme value identified by the user with the nearest non-extreme value in the dataset, according to the rank order of the extreme value. For example, the third extreme value will be replaced by the third non-extreme value, counting inwards from the extreme value threshold (Chen & Dixon, 1972). One hundred twenty-one extreme values, as identified by the boxplot analysis, were replaced according the Winsorization method. Skewness and kurtosis statistics also yielded values within the ideal -1 to 1 range. Although the transformed variable that excludes extreme outliers yields skewness and kurtosis statistics not very different from those of the Winsorized ones, preference is given to the Winsorized form

[12] "Severe [or extreme] outliers are defined as cases more than 3IQR beyond the first or third quartile" (Hamilton, 1992, p. 10).

because it does not reduce the number of cases under study. Only models with Winsorized outcome variables are described below.[13]

Table 7: Descriptive statistics for distance outcome variable

	Untransformed		**Natural log transformed**					
	Buyers	Sellers	Buyers			Sellers		
	All cases	All cases	All cases	Excl. extremes	Winsor.	All cases	Excl. extremes	Winsor.
Mean	3.57	2.79	-0.08	0.09	-0.04	-0.23	-0.08	-0.20
SD	6.15	4.88	2.05	1.75	1.9	1.96	1.69	1.83
Median	1.14	0.99	0.13	0.20	0.13	-0.01	0.04	-0.01
Min	0.00	0.00	-11.04	-5.18	-5.09	-13.12	-5.10	-5.10
Max	62.81	66.44	4.14	4.14	4.14	4.20	4.20	4.20
Skewness	3.36	4.10	-1.03	-0.32	-0.53	-0.98	-0.36	-0.56
Kurtosis	14.64	24.18	2.20	-0.31	0.03	1.87	-0.24	0.09
N	5,171	13,473	5,171	5,049	5,171	13,473	13,155	13,473

Table 8 below provides descriptive statistics of individual level variables used in the study. The average age for buyers and sellers is 30 and 33 years, respectively.[14] Thirty-seven percent of all drug buying arrests were for the purchase of marijuana, and 20% of selling arrests were for the same drug. Seven percent of arrests for buying and selling drugs were for narcotics. Crack cocaine appears to be a very popular drug of choice. Twenty-seven percent of buying arrests were for buying and 35% were for selling crack cocaine, compared to 6% and 7% for powder cocaine, respectively. Twenty-one percent of buying incidents and 30% of selling incidents were for heroin. Females were better represented among sellers arrested (17%) than buyers (12%). Turning to the race and ethnicity, it appears that African Americans composed roughly

[13] Alternative models excluding extreme values yielded similar results.
[14] Reflects the Winsorized form of the age variable. The original age variable contained a maximum age of 109 for buyers and 83 for sellers. Such ages were likely incorrectly recorded at the time of arrest. However, if they are correct they represent an atypical offender. Review of the frequency distributions of the age variable for buyers and sellers led to the decision to replace high-end values through Winsorising where the frequency of a particular age occurred less than 2% of the time.

60% of all buyers arrested, followed by whites (22%), and Hispanics (18%). Considering sellers, once again African Americans compose the largest proportion of the group (48%), then Hispanics (30%), and finally whites (20%).

Table 8: Individual level descriptives

	Mean		St. Dev.		Minimum		Maximum	
	Buyers	Sellers	Buyers	Sellers	Buyers	Sellers	Buyers	Sellers
Age	30.19	32.64	11.26	11.81	12.00	11	60	59
Marijuana	.37	.20	.48	.40	.00	.00	1.00	1.00
Narcotics	.07	.07	.26	.25	.00	.00	1.00	1.00
Powder cocaine	.06	.07	.25	.26	.00	.00	1.00	1.00
Crack cocaine	.27	.35	.45	.48	.00	.00	1.00	1.00
Heroin	.21	.30	.40	.46	.00	.00	1.00	1.00
Female	.12	.17	.33	.38	.00	.00	1.00	1.00
Hispanic	.18	.30	.38	.46	.00	.00	1.00	1.00
White	.22	.20	.41	.40	.00	.00	1.00	1.00
African American	.59	.48	.49	.50	.00	.00	1.00	1.00

Note: N = 5,171 (buyers), 13,473 (sellers).

Table 9 provides descriptive statistics of correlates aggregated to the drug market level. The age value below reflects the noted statistic pooled across markets. In other words, the median age value reflects the median of the median ages recorded at the drug market level. The median aggregate age value across markets for buyers and sellers is about 30 years and 33 years, respectively. The remaining predictors indicate the statistic percentage of the phenomenon characterized by each predictor, at the market level. Turning to buyers exclusively, the median percentage of arrests for marijuana is 39%, followed by crack cocaine (30%). The smallest median percentage is powder cocaine (5%). Females generally composed about 12% of buyers at the market level. In terms of race and ethnicity, the middle value for the proportion of African Americans across markets is 65%, followed by whites (14%), and Hispanics (11%). Turning to sellers, the middle range value for marijuana arrests is 19%, compared to the 40% for buyers. Yet compared to their buying counterparts for crack cocaine (30%), sellers at the market level had a much larger median score at 43%. Gender median proportions were not substantially different from one another across arrest types. However, when considering sellers' race and ethnicity the group with the second largest median score behind African Americans (62%) was Hispanics (16%), whereas when considering buyers, whites contained the second-largest median score.

Table 9 suggests that some drugs can be found at all drug markets. The minimum values for the proportion of marijuana and crack cocaine drugs indicates that across all drug markets sales and purchases for both drug types occurred. This was not the case for narcotics, powder cocaine, or heroin. On the other hand maximum value scores indicated that some drug markets specialized in certain drug types. For example, one drug market had 90% of its arrests for the sale of crack cocaine, and another market had 73% or its arrests for heroin sales. The maximum proportion for assumingly less popular drugs such as powder cocaine reached 43%, and 40% for narcotics.

Table 9: Market level descriptives

	Mean		St. Dev.		Median		Minimum		Maximum	
	Buyers	Sellers	Buyers	Sellers	Buyers	Sellers	Buyers	Sellers	Buyers	Sellers
Age	30.23	33.28	2.86	2.82	30.26	32.67	25.37	27.45	36.38	37.68
Marijuana	.39	.26	.17	.20	.40	.19	.07	.02	.75	.73
Narcotics	.07	.06	.05	.09	.06	.02	.00	.00	.20	.40
Powder cocaine	.06	.05	.05	.09	.05	.01	.00	.00	.24	.43
Crack cocaine	.30	.46	.14	.26	.30	.43	.06	.01	.58	.90
Heroin	.15	.17	.19	.21	.06	.07	.00	.00	.64	.73
Female	.12	.18	.04	.03	.12	.18	.05	.11	.21	.24
Hispanic	.18	.20	.19	.21	.11	.16	.00	.00	.60	.59
White	.18	.14	.17	.14	.14	.10	.00	.00	.61	.46
African American	.63	.64	.32	.31	.65	.62	.16	.19	1.00	1.00

Note: N = 34.

Bivariate Pearson correlation coefficients were produced to ensure that collinearity was not a problem among the independent variables, especially considering that each variable is computed at the individual level as well as the aggregate (market) level.

Separate matrices for drug buyers and sellers revealed interesting results. When considering drug buyer data, there was a strong negative correlation between the percentage of African American buyers and Hispanic buyers in a drug market ($r = -0.87$, $p < .01$). This finding that the likelihood of one group buying drugs in a drug market declines with the increasing presence of another may be suggestive of the residential settlement patterns of African Americans and Hispanics in Philadelphia. In a similar vein, there was a significant negative correlation between the proportion of African American buyers and white buyers within drug markets ($r = -0.89$, $p < .01$). Additionally, Pearson *r* values suggest that drug markets concentrated with white buyers were unlikely to have a high proportion of marijuana purchases ($r = -0.77$, $p < .01$). On the other hand, there was a strong significant correlation between the proportion of white buyers in a drug market and heroin purchases providing preliminary evidence of drug preference by race/demographic links ($r = 0.92$, $p < .01$). Markets with a high proportion of African American buyers however, were unlikely to have high proportions of heroin purchases ($r = 0.82$, $p < .01$). Lastly, it appears that there may be drug specialization by market. Drug markets with high proportions of marijuana drug buying arrests were likely to have a *low* proportion of heroin arrests ($r = 0.86$, $p < .01$).

A few similar patterns emerge when reviewing correlations among drug seller variables. First, there was a negative correlation between the percentage of African-

American drug sellers and Hispanic sellers within markets (r = -0.88, p < .01). Therefore, not only were African-Americans and Hispanics unlikely to buy drugs in the same drug markets, they were also unlikely to sell drugs in the same markets. Second, similar to their drug buying counterparts, African-American sellers were unlikely to be found in markets that sold high proportions of heroin (r = -0.71, p < .05). The proportion of white sellers however, demonstrated a significant positive correlation with the proportion of heroin sales (r = 0.88, p < .01). Also as seen in the case of drug buyers, there was a negative correlation between the proportion of marijuana and heroin sales within markets (r = 0.71, p < .01).

On the other hand there are noteworthy differences seen in the correlation matrix of sellers as compared to buyers. First, the average age of drug sellers within drug markets was positively correlated with the percentage of African-American sellers (r = 0.70, p < .01). Second, there was a strong positive correlation between the proportion of African American sellers and the proportion of crack cocaine sales (r = 0.74, p < .01). This is not surprising considering previous research documenting the presence of crack cocaine drug markets in inner-city African American neighborhoods (Anderson, 1999).

Significant correlations among items pose problems for regression modeling. Principal components analysis presents an avenue by which to combine similar items, however, such an approach would prevent this research from understanding the unique contribution of each predictor to account for variation in the outcome variable. Fortunately, there were no instances in which a variable at the individual level correlated strongly with its aggregate version at the market level. Multicollinearity tests revealed interrelatedness among some of the variables described, and thus constrained model designs. Variance inflation factor and tolerance scores for all predictors within *reported* models are less than 4 and greater than 0.4, respectively.

HLM models

Separate HLM ANOVAs were run for both buyer and seller distance to see if, for each group of arrestees, distance varied significantly at the market level. Results (shown in Table 10) indicated significant market-level variation in average logged distance (p < .001) for both buyers and sellers. High reliability suggests the Empirical Bayes estimates of market averages are good approximations of "true" average distances traveled. Intraclass correlations revealed that 6% and 4% of distance variation was located at the market level for buyers and sellers, respectively.

Table 10: ANOVA results of buyer and seller distance variables

	Buyers				Sellers			
Fixed	**β**	**exp(β)**			**β**	**exp(β)**		
Average travel distance	-0.16	0.85			-0.37	0.69		
Random	**σ^2**		**χ^2**		**σ^2**		**χ^2**	
Between market variation	0.22	***	519.28	***	0.14	***	756.30	***
Individual remaining variation	3.32				3.22			
Reliability	0.87				0.92			
Intraclass correlation	0.06				0.04			
Deviance	20964.30				54100.56			
Parameters	2.00				2.00			

Notes: N = 5,171 buyers, 13,473 sellers. *Df* = 33. *** p <.001. Distance logged and winsorized.

Table 11 displays results for hierarchical linear models predicting drug buyer travel distance. Model 1 examines the impact of drug buyer individual level correlates on travel distance. Model 2 adds in individual level drug choice correlates. Model 3 controlled for fixed market level influences. All models control for market random effects. Model 1 shows that there is a significant positive relationship between the age of the drug buyer and travel distance to arrest location. Considering that age is a grand mean centered variable, for every additional year in age above average age it increases the natural log of travel distance by .01. In line with prior research (Groff & McEwen, 2005; Pettiway, 1995) females travel less far than male drug buyers. Research has not explained why females generally stay closer to home in their offending patterns. Perhaps childrearing duties prevent longer trips. When considering race and ethnicity, Hispanics compared to those in the reference group travel less far ($\beta = -0.67$, $p < .001$) than African American males of average age. Whites however, travel the farthest of the groups included in the model ($\beta = 1.35$, $p < .001$). The significant chi-square value associated with residual outcome variation at the market level suggests additional compositional or market level mediators would be appropriate.

Model 2 of Table 11 adds in drug choices. Choice renders drug buyer age marginally significant. Narcotics ($\beta = .30$, $p < .01$) and powder cocaine buyers ($\beta = .32$, $p < .01$) travel farther than reference group members. The travel distance to arrest for crack cocaine buyers however, is not significantly different from African American male marijuana buyers (reference string). In line with past research, heroin buyers travel significantly farther than buyers of other drugs (Forsyth, et al., 1992).

Model 3 adds drug market level influences. Percentage of African American buyers within drug markets is included. Gender is now non-significant. The individual level race predictor must be removed due to collinearity. Results indicate that as the proportion of African American buyers within drug markets increases, travel distance decreases ($\beta = -1.17$, $p < .001$).

Additional models (See Appendix B) examine how market level correlates influence individual level travel decisions to buy drugs. Models reveal that the proportion of arrests for each drug type, gender mix, average age, ethnicity proportions, and the percentage of white buyers within drug markets have no significant effect on individual level travel distance.

Table 12 presents models parallel to Table 11 predicting drug *seller* travel distance. Model 1 shows that the same correlates that constrain buyer distance also affect sellers. Older ($\beta = 2.80E\text{-}3$, $p < .05$), and white drug sellers ($\beta = 1.24$, $p < .001$) generally travel farther to their arrest locations than African American male drug sellers. Females and Hispanics travel shorter distances than the reference group.

Controlling for drug type (Model 2, Table 12) shows narcotics and heroin sellers had longer trips to arrest. Unlike Model 2 for predicting buyers age remains significantly linked to longer distances predictor ($\beta = 3.29E\text{-}03$, $p < .05$).

Finally, Model 3 incorporates the percentage of African American sellers within each drug market. As with the buyer model, proportion of African American sellers links negatively with sellers' travel distance.

Additional seller models incorporating other market level predictors are considered (Appendix B). At the market level compositional, drug type, gender, and age predictors did not explain differences in sellers' distances.

Table 11: HLM models predicting drug buyer travel distance

	Model 1				Model 2				Model 3			
	β		SE	*t*	β		SE	*t*	β		SE	*t*
Intercept	-0.27		0.08		-0.36		0.07		0.64		0.15	
Individual												
Age	0.01	*	2.17E-03	2.52	4.22E-03	†	2.23E-03	1.90	4.29E-03	†	2.28E-03	1.89
Female	-0.18	*	0.07	-2.41	-0.16	*	0.07	-2.22	-0.05		0.07	-0.65
Hispanic	-0.67	***	0.08	-8.66	-0.71	***	0.08	-9.24	-1.31	***	0.07	-18.33
White	1.35	***	0.07	18.46	1.19	***	0.07	15.89				
Narcotics					0.30	**	0.10	3.04	0.36	***	0.10	3.53
Powder cocaine					0.32	**	0.11	3.06	0.40	***	0.11	3.74
Crack cocaine					-0.06		0.06	-0.93	-0.04		0.06	-0.59
Heroin					0.61	***	0.08	7.63	0.86	***	0.08	10.69
Market												
African American (%)									-1.17	***	0.20	-6.00
Level 1 σ^2	2.93				2.89				3.02			
Level 2 σ^2	0.15				0.11				0.09			
χ^2	355.79	***			258.14	***			183.46	***		
Deviance	20319.97				20252.52				20466.85			
Parameters	2.00				2.00				2.00			

Notes: N = 5,171. † *p* <.06, * *p* <.05, ** *p* <.01, *** *p* <.001.

Table 12: HLM models predicting seller travel distance

	Model 1				Model 2				Model 3			
	β		SE	*t*	β		SE	*t*	β		SE	*t*
Intercept	-0.37		0.07		-0.42		0.07		0.46		0.13	
Individual												
Age	2.80E-03	*	1.27E-03	2.20	3.29E-03	*	1.28E-03	2.57	4.82E-03	***	1.31E-03	3.67
Female	-0.34	***	0.04	-8.78	-0.34	***	0.04	-8.71	-0.22	***	0.04	-5.49
Hispanic	-0.56	***	0.04	-14.00	-0.57	***	0.04	-14.50	-1.07	***	0.04	-29.31
White	1.24	***	0.04	27.60	1.18	***	0.05	26.03				
Narcotics					0.53	***	0.07	7.78	0.55	***	0.07	7.91
Powder cocaine					0.15	*	0.07	2.23	0.28	***	0.07	3.95
Crack cocaine					-0.07		0.04	-1.59	-0.07		0.05	-1.45
Heroin					0.28	***	0.05	5.54	0.47	***	0.05	8.99
Market												
African American (%)									-1.06	***	0.17	-6.15
Level 1 σ2	2.86				2.84				2.98			
Level 2 σ2	0.14				0.11				0.08			
χ2	710.32	***			479.63				253.10	***		
Deviance	52529.42				52427.56				53056.48			
Parameters	2.00				2.00				2.00			

Notes: N = 13,473. * p <.05, ** p <.01, *** p <.001.

Discussion

Chapter 4 of the dissertation sought to examine how individual and contextual predictors account for variation in travel distance to buy and sell illicit substances in spatially identified drug markets while simultaneously controlling for market destination. Only three studies to date have analyzed the travel distances of drug offenders (Forsyth, et al., 1992; Johnson, et al., under review; Pettiway, 1995)—all of which left many questions unanswered. The current work addressed outstanding questions by using a hierarchical linear model to examine the travel distances of roughly 5,000 drug buyers and 13,000 sellers arrested from 2006 through 2010 by the Philadelphia Police Department. Exploratory data analysis revealed that drug offenders, like many other offenders do not travel far to the offense location. Drug buyers have a median travel distance to arrest of 1.14 miles while sellers travel .99 miles. It is not clear from these aggregate numbers whether buyers and sellers engage in differential search patterns. Qualitative research may better address differences in search patterns between buyers and sellers. Themes accounting for variation around the median travel distances for both groups are highlighted below.

Demographics

Prior journey to crime research has highlighted the importance of individual-level demographics for explaining crime journeys but has not considered differences between buyers and sellers. Findings here add to prior research by showing that the importance of individual demographics is relative to whether the arrestee is a buyer or seller, as well as drug type. Specifically, when only considering the influence of individual-level demographics, findings of prior research are confirmed in that older individuals travel significantly farther than younger ones to *purchase* drugs. However, the meaningfulness of age is diminished in drug buying models when individual level drug choices and drug market level forces are factored. Conversely, when considering the travel distances of sellers age (older individuals traveling farther) is a consistently significant indicator of travel distance. In a similar sense when analyzing seller travel distance real differences between the distances of females and males emerge regardless of additional considerations. Real gender differences are also evident when examining buyers with females traveling shorter distances (but gender becomes a *non-factor* when considering the *proportion* of African-American buyers in drug markets). This finding lends support to research by Griffin and Rodriguez (2011) finding that women are more likely to acquire marijuana and crack in their neighborhoods than men.

Other trends were observed for both drug buyers and sellers. This research has lent support to earlier findings that minorities travel less far than whites. But a new finding is ethnicity impacts for drug sellers. Hispanics travel less far than whites to sell and buy drugs.

When considering the overall market racial dynamics, it appears that markets with higher proportions of African-American drug offenders are likely to have individuals traveling shorter travel distances. This may suggest that in a comparative sense Philadelphia African-Americans are much more likely to live within or very close to areas of concentrated drug sales. Indeed, the proportion of African Americans residing in Chapter 3's spatially outlined drug markets ranged from 16-100%, as compared to 0-61% for whites and 0-60% for Hispanics. Alternative possible explanations are that it may be more difficult for African Americans from outside of Philadelphia to reach Philadelphia drug markets than their white counterparts. It is also possible that African Americans from outside of Philadelphia know where to find local drug markets but their white counterparts do not.

Drug choice

When considering how drug choice correlates with travel distance, results confirm Forsyth and colleagues' (1992) finding that heroin buyers travel farther than those purchasing other drug types. Nonetheless, this is the first study to examine how drug type correlates with travel distance for drug *sold*. Although modeling showed that heroin sellers travel farther than marijuana sellers, coefficients revealed that they travel less far than narcotics sellers—the drug type for sellers associated with the longest travel distance. Also interesting are findings about cocaine drug offenders. While those arrested for buying or selling powder cocaine travel significantly farther than marijuana drug offenders, *crack* cocaine drug offenders travel about the same distance as marijuana drug offenders—the drug type with the *shortest* travel distance. The above findings indicate that drug type is a real indicator of drug offender travel distance.

Limitations

The current work has limitations. First, this work makes the assumption that the travel route for drug offenders originated at the home and ended at the arrest location, via the street network. Given a quantitative research approach and large numbers of cases it is the best currently available solution for studying distance to crime. Second, it was not possible to verify that the arrest location was the drug purchase location. Arresting officers may have witnessed the transaction at one location, yet allowed the arrestee to travel to a location safer for conducting the arrest.

Potentially partially offsetting these limitations were several study strengths. First, geocodable drug arrests for a five-year period from the fifth largest city in the United States were analyzed. This resulted in a sample that was larger than prior research on the subject. This sample was multi-racial and multi-ethnic, and included suburban as well as urban buyers on trips to buy a variety of drugs. Second, the design of this research is such that it focused on travel decisions to large drug markets—the first of its kind to the author's knowledge and an addition to recent research considering crime in agglomeration economies (Taniguchi, et al., 2009). Fourth, this research analyzes only the first trip within the study period by each offender to avoid changes in criminal decision-making over time resulting from prior contacts with the criminal justice system during the study period. The next chapter will develop this research further by separately examining the impact of drug buyer and seller travel distance on within-drug market violence.

CHAPTER 5:

JOURNEYS TO BUY AND SELL DRUGS IMPACT ON WITHIN MARKET VIOLENCE

Introduction

Chapter 5 builds Chapters 3, which defined markets and 4 which investigated determinants of travel distance to markets. Thus the focus of this chapter is on predicting violent crime counts within drug markets. This is done by separately modeling the effects of buyer and seller distance on within-market violence. Most importantly, this chapter provides the prelude to the full test of Reuter and MacCoun's (1992) hypothesis in Chapter 6.

It is possible that interacting buyers and sellers from varying distances within drug markets conflict to produce violence in such areas. It is also possible that an interaction between buyers and sellers is unnecessary for violence to take place. Buyers may have established social ties within their neighborhoods useful for acquiring drugs peacefully. As they seek drugs outside of their neighborhood it is possible that as the likelihood of social ties decreases, so too does one's understanding of the local norms for acquiring drugs. The lack of awareness on behalf of the buyer and seller may link to violent conflicts as neither party knows the other well enough to conduct the transaction without a high level of anxiety.

The distance of drug dealers—aside from that of buyers—may have implications for drug market violence if it suggests drug market instability through territory encroachment. In other words, dealers seeking selling territory outside of their home neighborhoods may be more likely to engage in violent conflict with the local dealers of new territories. Both scenarios suggest that there should be a main effect of distance on within-market violence. These possibilities are investigated in the current chapter of the dissertation.

Wilcox and Eck (2011) have argued that although certain categories of land uses serve as crime generators, only a small proportion of land uses within each category generates a high amount of crime. In a similar vein outdoor drug markets as well are known for undesirable side effects (namely violence), but this research will show that there is substantial variation in violence levels across drug markets.

Methodology

Data

Violent crime incidents were also extracted from the incident database for analysis. During the study period, 72,881 (72,881 cases in total; 71,849 with valid X/Y coordinates) violent incidents occurred in the city. These offenses include homicides, robberies, and aggravated assaults (see Table 13). Rape offenses are excluded, as a review of the literature has provided no theoretical reason to believe that such crimes would correlate with the travel distances of drug offenders. Conversely, homicides, robberies, and aggravated assaults are offenses that were described in the literature as *instrumental* in acquiring or selling drugs. [15]

[15] It is important to note that drug offender violence is likely to suffer from underreporting, considering that both the victim and offender are involved in illegal activity (Goldstein, 1985; Gottfredson & Gottfredson, 1988). In turn, drug offender robbery events are less likely than other violent crimes to appear in official data and may not lend themselves well to quantitative research using official data. On the other hand, more

Table 13: Violent UCR codes used in analyses

UCR Code	Crime description
100 series	**Homicide**
	Criminal homicide
111	By handgun
112	By rifle
113	By shotgun
114	By knife/cutting instrument
115	By beating - hands, fists, feet, etc.
116	Other
	Manslaughter-Gross negligence
121	By conveyance-With an arrest (auto, bike, train, trolley, etc.)
122	Other than by conveyance
123	By conveyance- No arrest (auto, bike, train, trolley, etc.)
300 series	**Robbery**
	On the highway
300	By handgun
301	By shotgun
302	By rifle
303	By knife/cutting instrument
304	Other dangerous weapon
305	No weapon (strong arm robbery)
	Purse snatch, force or injury
306	$50.00 or over
307	$5.00 to $49.99
308	Under $5.00
	Of residence
350	By handgun
351	By shotgun
352	By rifle
353	By knife/cutting instrument
354	Other dangerous weapon
355	No weapon (strong arm robbery)
	Of vehicle
388	By handgun
389	By shotgun
396	By rifle

serious forms of victimization resulting in bodily harm (including violent robberies) are more likely to be reported to the police (Gottfredson & Gottfredson, 1988). Therefore, one would expect that violent events resulting in serious injury compose most of the cases within official data related to drug market violence.

Table 13, continued: Violent UCR codes used in analyses

397	By knife/cutting instrument
398	Other dangerous weapon
399	No weapon (strong arm robbery)
	Miscellaneous situations not listed
390	By handgun
391	By shotgun
392	By rifle
393	By knife/cutting instrument
394	Other dangerous weapon
395	No weapon (strong arm robbery)
400 series	**Aggravated assault**
	Aggravated assault
411	By handgun
412	By shotgun
413	By rifle
414	By knife/cutting instrument
415	Other dangerous weapon
416	By hands, fists, feet, etc.

Source: Philadelphia Police Department (2001).

Variables

Outcome

Drug market violence is operationalized as the number of violent incidents (see Table 13) that occurred within a drug market. Crime in each of the 34 drug markets is assessed by year (2006, 2007, 2008, 2009, and 2010). Yearly violence counts are nested within drug markets.

This approach allows the separation of temporal differences by year from stable market-level differences visible over the entire period. Inherent in this operationalization is the assumption that drug market boundaries are stable over the five-year period, because they were generated using all five years of incident data (2006-2010). The theoretical advantage to this approach is that it allows this dissertation separate temporal variation from stable market differences.

Time-varying covariates

It is expected that a number of time-varying covariates may account for temporal variation in violence over the five-year study period. Impacts of predictors for each year are expected to link to within-market violence for the same year. Temporal lag effects are not modeled or expected. Changes in aggregate buyer or seller distance composition are reflective of changes in the people associated with drug markets. Such changes are highly visible (unlike changes in community socioeconomic status) and expected to connect with violent conflicts due to the kinds of interactions described in the introduction of this chapter. Yearly dummy variables with 2006 as the reference string are included.

The mean age of drug sellers, proportion of female sellers, percentage of minority sellers, and median seller distance were modeled as separate covariates.[16]

Additional covariates indicated the proportion of sellers arrested for marijuana, powder cocaine, crack cocaine, heroin, or manufactured narcotics (Demerol, methadone).

Every drug market was assigned a value for each of the above time-varying covariates, for each of the five years of the study. Like variables were constructed for drug buyer models.

A series of time-varying indicators for demographics known for to correlate with crime were used as proxies for community dynamics occurring within drug markets. A value for each indicator listed below was calculated at the block group level for each of the five years in the study:

<u>Socioeconomic status</u>
The following variables were z-scored and averaged: proportion of households with incomes at or above $35,000, proportion of individuals 25 years or older with at least a high school education, median home value, and median household income.

<u>Stability</u>
The following variables were z-scored and averaged: proportion of owner-occupied housing units and the proportion of long-time residents.[17]

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[16] The median travel distance is used because it is less susceptible to skewed distributions commonly found in journey to crime research (Groff & McEwen, 2005).
[17] The long-time residents variable was derived from GeoLytics Estimates Premium and reflects those at least five years of age that have resided in the same home at least five years earlier. It is a ratio of long-term residents in the United States to those in each block group. Admittedly this is a non-traditional proxy for long-term residency; however, as shown in <u>Table 14</u> the other data sources lack the traditional form of the long-term residency variable for the years needed.

Heterogeneity

Racial heterogeneity is a measure computed "as one minus the sum of the squared proportion of residents in each racial/ethnic category" (Bellair & Browning, 2010, p. 507). Four racial groups were included in this measure: African Americans, Hispanics, Asians, and Non-hispanic whites.[18]

Age

The proportion of the population aged 10-24.

Family structure

The following variables were z-scored and averaged: proportion of married households, proportion of non-single person households, and the proportion of married households with children.

Census data and estimates

The multi-year (2006-2010) design of this study requires correlates that reflect changes over time, on a yearly basis. The U.S. Census Bureau produces tabulations in its decennial census of population and housing based counts in its Summary File 3 tables at the block group level (U.S. Census Bureau, 2000). Those tabulations however, are outside of the study period of this dissertation. The American Community Survey (ACS) collects population and housing data on a yearly basis, yet it excludes some of the variables tabulated in the decennial census (U.S. Census Bureau, 2008). Additionally ACS releases 1-year, 3-year, and 5-year estimates for each year. For example, current 5-year data were collected from 2005-2009. Five-year estimates are used in this research because only the 5-year estimates provide data at the block group level. To clarify, 5-

[18] African Americans include Hispanic and Non-hispanic African Americans. Asians reflect Hispanic and Non-hispanic Asians, Hispanic and Non-hispanic Hawaiians, and Pacific Islanders. Hispanics include Hispanic whites, Hispanic others, and Hispanics that self-classify under two or more races. Whites are considered Non-hispanic whites.

year estimates do not provide estimates for every year in the 5-year study period. They merely provide estimates for population and housing variables using data collected over the 5-year period. Also, only the 5-year estimates are available at the block group level.

Due to the limitations of the decennial census and ACS, GeoLytics was employed to pull some of the demographic data presented here. Currently, GeoLytics provides postcensal estimates of decennial census data for each of the years spanning 2001-2008. When available, variables were pulled from GeoLytics for this study for 2006-2008—the years of the current study also covered by GeoLytics. Additional information on GeoLytics' estimation methodology can be found in Appendix D.[19]

Because no one data source provided data for each of the five years included in this study, intercensal estimation was used to fill in missing data.[20] In this research, intercensal estimates were computed using the arithmetic rate of change formula:

$$Annual\ net\ change = \frac{P_{07} - P_{00}}{n}$$

Where: P_{07} is the 2007 mid-point population of the 2005-2009 ACS population

P_{00} is the 2000 census population

n is the number of years between the two census periods

[19] There are two major limitations of postcensal estimation techniques. The first is that estimates for larger areas will be more accurate than estimates for smaller ones. This is because much of the error associated with estimates for smaller areas can be smoothed out when aggregated to larger areas. The second limitation has to do with the extent of population change in an area. Those areas that have experienced substantial population change will have estimates with larger amounts of error than areas with less substantial population change (Raymondo, 1992).

[20] Intercensal estimation is the process of calculating population and population-based estimates for time points between census years (Raymondo, 1992).

Therefore, the arithmetic rate of change formula calculates the difference in population for two periods, and then divides that value by the number of years between the two census collection periods. This annual net change value can then be added to P_{00} to produce an estimate of the 2001 population. The annual net change value can then be added to the 2001 estimate to estimate the 2002 population. This process is repeated until all intercensal years have been estimated.[21]

Table 14 displays variables used to construct the above indices derived from the decennial census, GeoLytics, and ACS via intercensal estimation. Notations within each column indicate the availability of a variable for a respective year. For example, data on the total number of Non-hispanics were available for the year 2000 via the decennial census and the ACS tabulated from 2005-2009. For the purpose of this research it was assumed that the ACS data would be a good reflection of its time mid-point (2007).

[21] Inherent in the arithmetic rate of change approach to intercensal estimation is the assumption that actual rate of change has been constant over time. Such an assumption is likely to be false. Furthermore, as an interpolation technique intercensal estimation most appropriate for dealing with total population variables, rather than other demographic variables (Raymondo, 1992).

Table 14: Variable interpolation

Variable Description	**Census**	**Projections**					**ACS**
	2000	***2006***	***2007***	***2008***	***2009***	***2010***	*2005-2009*
Total Population	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Race and ethnicity							
Not Hispanic	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Not Hispanic: White	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Not Hispanic: African American	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Not Hispanic: American Indian	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Not Hispanic: Asian	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Not Hispanic: Hawaiian or Other Pacific Islander	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Not Hispanic: Some other race alone	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Not Hispanic: Two or more races	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Hispanic	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Hispanic: White	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Hispanic: African American	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Hispanic: American Indian	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Hispanic: Asian	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Hispanic: Hawaiian or Other Pacific Islander	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Hispanic: Some other race alone	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Hispanic: Two or more races	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Residential stability							
Total Population: 5 years and over	Yes	No	No	No	No	No	No
Total Population: 5 years and over: Same house 5 years earlier	Yes	Yes	Yes	Yes	Int.	Int.	No
Total Population: 5 years and over: Different house 5 years earlier	Yes	Yes	Yes	Yes	Int.	Int.	No
Educational attainment							
Population 25+	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Total Male Population: 25 years and older	Yes	Yes	Yes	Yes	Int.	Int.	
Male: Some college, Less than 1 year	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Male: Some college, 1 or more years, no degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Male: Associate's degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Male: Bachelor's degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Male: Master's degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Male: Professional school degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Male: Doctorate degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Total Female Population: 25 years and older	Yes	Yes	Yes	Yes	Int.	Int.	
Female: Some college, less than 1 year	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Female: Some college, 1 or more years, no degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes

Table 14, continued: Variable interpolation

Female: Associate's degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Female: Bachelor's degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Female: Master's degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Female: Professional school degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Female: Doctorate degree	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Housing and households							
Total Occupied Housing Units	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Total Owner Occupied Housing Units	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Total Renter Occupied Housing Units	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Median Home Value for Owner Occupied Housing Units	Yes	Int.	Int.	Int.	Int.	Int.	Yes
Median Household Income in 1999	Yes	Yes	Yes	Yes	Int.	Int.	Yes
Age							
Population aged 10-24	Yes	Yes	Yes	Yes	Int.	Int.	
Family structure							
Married households		Yes	Yes	Yes	Int.	Int.	
Married households with children		Yes	Yes	Yes	Int.	Int.	
Single person households		Yes	Yes	Yes	Int.	Int.	

Note: Int. - variable was interpolated for that particular year.

Principal components analysis

The city of Philadelphia is composed of 1,816 blocks groups. Block groups with less than 25 residents for any year of the study were excluded from subsequent analysis, leaving a total of 1,721 block groups. Principal components analysis with a varimax rotation was used to confirm sets of variables that when combined represent the underlying constructs of indices described above. Table 15 displays data on the principal component analyses for the z-scored index variables, by year.[22] Principal component analysis was used to provide evidence of internal consistency. Across years and constructs Cronbach's alpha yielded values of at least .72. According to Meyers, Gamst, and Guarino (2006) the KMO statistic is a measure of whether there is enough correlation among the items to produce reliable factor analysis results. Values above .7 are ideal

[22] Principal component analysis was used to provide evidence of internal consistency. Z-scores of index variables (not principal component analysis scores) were used in regression analyses discussed later in the chapter.

(Kaiser, 1974). Table 15 shows that the stability and family structure indices fell below that threshold with values of .5 and .58, respectively. Nonetheless, these values met the *minimum* standard necessary (.5) for accepting the reliability of factor analysis results (Kaiser, 1974).

Table 15: Component loadings for indices used in the study

	2006	2007	2008	2009	2010
Socioeconomic status					
Keyser-Meyer-Olkin measure of sampling adequacy	0.73	0.729	0.724	0.722	0.72
% of households w/ incomes > $35,000	0.904	0.905	0.906	0.906	0.906
% of residents over 25 years with at least a high school education	0.834	0.835	0.833	0.83	0.829
Median home value	0.728	0.715	0.703	0.688	0.678
Median household income	0.908	0.907	0.91	0.909	0.908
Cronbach's α	0.865	0.862	0.858	0.853	0.849
N	1,616	1,618	1,614	1,608	1,607
Stability					
Keyser-Meyer-Olkin measure of sampling adequacy	0.5	0.5	0.5	0.5	0.5
% Owner-occupied housing units	0.892	0.892	0.892	0.892	0.892
Long-time residency	0.892	0.892	0.892	0.892	0.892
Cronbach's α	0.742	0.742	0.742	0.742	0.742
N	1,714	1,714	1,714	1,714	1,714
Family structure					
Keyser-Meyer-Olkin measure of sampling adequacy	0.58	0.58	0.58	0.58	0.58
% 2+ person households	0.604	0.604	0.602	0.601	0.599
% Married family, 2+ person households	0.888	0.886	0.887	0.888	0.888
% Married households with children	0.904	0.903	0.903	0.903	0.903
Cronbach's α	0.724	0.723	0.722	0.722	0.721
N	1,707	1,706	1,705	1,705	1,705

Note: Bartlett's test of sphericity $p <. 001$ across all indices and years.

Missing data and multiple imputation

Descriptive statistics revealed that missing data was evident for three variables (see Appendix E). The family structure variable was missing .8% cases in 2006 and .9% of cases each year thereafter. The stability construct was also missing data, yet only .4% of cases for each year of the study. More problematic, was that between 6% and 6.6% of cases were missing for the socioeconomic status variable. To address this concern, a more in depth analysis of missing data was conducted.

Separate-variance *t*-tests indicated that the missingness of socioeconomic status had an impact on a number of other demographic constructs, namely family structure and stability (see Table 16). In other words, the mean values of the listed demographic constructs were significantly different when comparing cases with recorded socioeconomic status values to those without socioeconomic status values. Little's (1988) MCAR test yielded a significant *F*-statistic, $F(385) = 597.617$, $p < .001$, which confirms the data are not MCAR. Little's test was run on the pooled dataset reflecting the entire study period because the missingness of a variable in one year could be linked to the missingness of another variable in a subsequent year.

Table 16: T-tests of socioeconomic status missingness

	Family structure					Stability					SES				
	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010
2006															
t	7.57	7.55	7.68	7.78	7.84	13.89	13.90	13.90	13.90	13.90	.	-3.67	.	.	.
df	100.44	100.41	100.58	100.73	100.85	106.98	106.99	106.99	107.00	107.01	.	1.00	.	.	.
p (2-tail)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	0.170	.	.	.
# Present	1614	1613	1612	1612	1612	1616	1616	1616	1616	1616	1616	1616	1613	1608	1607
# Missing	93	93	93	93	93	98	98	98	98	98	0	2	1	0	0
Mean (Present)	0.04	0.04	0.04	0.04	0.04	0.08	0.08	0.08	0.08	0.08	0.03	0.03	0.03	0.02	0.02
Mean (Missing)	-0.67	-0.66	-0.67	-0.67	-0.67	-1.23	-1.23	-1.23	-1.23	-1.23	.	2.03	1.45	.	.
2007															
t	7.63	7.61	7.75	7.84	7.91	14.17	14.17	14.18	14.18	14.17	.	.	.	.	.
df	98.18	98.15	98.32	98.47	98.58	104.86	104.86	104.87	104.88	104.88	.	.	.	.	.
p (2-tail)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.	.	.	.
# Present	1616	1615	1614	1614	1614	1618	1618	1618	1618	1618	1616	1618	1614	1608	1607
# Missing	91	91	91	91	91	96	96	96	96	96	0	0	0	0	0
Mean (Present)	0.04	0.04	0.04	0.04	0.04	0.08	0.08	0.08	0.08	0.08	0.03	0.03	0.03	0.02	0.02
Mean (Missing)	-0.67	-0.67	-0.68	-0.68	-0.68	-1.25	-1.25	-1.25	-1.25	-1.25	.	.	.	.	.
2008															
t	7.11	7.09	7.23	7.32	7.39	13.36	13.36	13.36	13.36	13.36	-4.12	-6.22	.	.	.
df	102.15	102.12	102.28	102.45	102.57	108.65	108.65	108.66	108.67	108.67	2.01	3.02	.	.	.
p (2-tail)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.050	0.010	.	.	.
# Present	1612	1611	1610	1610	1610	1614	1614	1614	1614	1614	1613	1614	1614	1608	1607
# Missing	95	95	95	95	95	100	100	100	100	100	3	4	0	0	0
Mean (Present)	0.04	0.04	0.04	0.04	0.04	0.08	0.08	0.08	0.08	0.08	0.02	0.02	0.03	0.02	0.02
Mean (Missing)	-0.64	-0.64	-0.64	-0.65	-0.65	-1.21	-1.21	-1.21	-1.21	-1.21	2.25	2.31	.	.	.

Table 16, continued: T-tests of socioeconomic status missingness

	Family structure					Stability					SES				
	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010
2009															
t	6.84	6.84	6.95	7.02	7.07	13.10	13.11	13.14	13.16	13.18	-8.72	-10.45	-8.61	.	.
df	108.73	108.72	108.86	108.99	109.09	115.42	115.42	115.46	115.50	115.53	7.10	9.19	5.08	.	.
p (2-tail)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.
# Present	1606	1605	1604	1604	1604	1608	1608	1608	1608	1608	1608	1608	1608	1608	1607
# Missing	101	101	101	101	101	106	106	106	106	106	8	10	6	0	0
Mean (Present)	0.04	0.04	0.04	0.04	0.04	0.08	0.08	0.08	0.08	0.08	0.02	0.02	0.02	0.02	0.02
Mean (Missing)	-0.61	-0.61	-0.61	-0.62	-0.62	-1.17	-1.18	-1.18	-1.18	-1.18	2.09	2.07	1.91	.	.
2010															
t	6.78	6.78	6.88	6.95	7.00	13.04	13.04	13.07	13.09	13.11	-9.05	-10.71	-9.30	.	.
df	109.92	109.91	110.05	110.19	110.28	116.61	116.61	116.65	116.68	116.71	8.13	10.24	6.13	.	.
p (2-tail)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.
# Present	1605	1604	1603	1603	1603	1607	1607	1607	1607	1607	1607	1607	1607	1607	1607
# Missing	102	102	102	102	102	107	107	107	107	107	9	11	7	1	0
Mean (Present)	0.04	0.04	0.04	0.04	0.04	0.08	0.08	0.08	0.08	0.08	0.02	0.02	0.02	0.02	0.02
Mean (Missing)	-0.60	-0.60	-0.61	-0.61	-0.61	-1.16	-1.16	-1.17	-1.17	-1.17	2.02	2.01	1.84	1.47	.

Missing data can be problematic because they have the potential to introduce bias into statistical results. If the data were MCAR, then the problem of missingness would be randomly distributed across the dataset and could be addressed using listwise deletion (Regoeczi & Riedel, 2003). A less stringent assumption is that the data are missing at random (MAR) which would suggest that missingness on one variable is due to the values of another variable in the dataset. If the data are not MCAR and not MAR they are considered not missing at random (NMAR) and thus non-ignorable (Regoeczi & Riedel, 2003). Statistical tests to confirm MAR are lacking (Sinharay, Stern, & Russell, 2001). Visual inspection of the data however, does not suggest that the missingness of cases on socioeconomic status is due to values on another variable in the dataset. This suggests that the data are non-ignorable.

Multiple imputation was chosen as the technique to address all missing data. Conceptually, multiple imputation uses Bayesian modeling to generate likely values for missing cases through a series of iterations (or imputations) (Sinharay, et al., 2001). Once multiple values are generated for each case, they are combined to generate a replacement value. Combining multiple generations of values for one missing case considers the error produced by each missing case (Sinharay, et al., 2001). The assumptions of the multiple imputation model are that the model parameters account for observed and missing cases, that the distribution prior to imputation is specified, and that the empty cases are missing at random. Unfortunately, there is no way to verify if this is true. The use of secondary data prevents this research from understanding the true reason as to why the U.S. Census Bureau failed to report values for certain block groups, although it is possibly due to interests in confidentiality and privacy.

Areal interpolation

Such data traditionally provided by the decennial census and aggregated to features such as block groups and tracts are incongruent with this study's drug market features. To address this problem, an areally-weighted technique was used to extract a value for a variable relative to each block group's contribution to a drug market area (Ratcliffe & McCullagh, 1999; Zhang & Qiu, 2011). Specifically, GIS was used to cut portions of census block groups that form the area of drug market polygons. The vicinity tool was used to measure the proportion of area within each drug market that the truncated block groups compose. A weighted value was computed for each truncated block group within a drug market, based on its proportional area. Finally, an average was computed across all truncated block groups within each drug market feature to produce a local value for each drug market.

Analysis

The nature of these data with years nested within markets calls for a hierarchical linear model (HLM) whereby the impacts of two levels of data can be assessed (Raudenbush & Byrk, 2002). By year, drug sellers or buyers are attached to the drug market where they were arrested. This allows this work to examine whether market-level buyer or seller typical distance links to violence for the same year, controlling for demographic context and broad year to year changes.

Based on prior violent crime research, and the skew of the violence variable discussed (see below) Poisson generalized HLM was used. The Poisson distribution is especially suited for counts of events which are relatively rare. Most cases will not experience the measured phenomenon and very few will experience it disproportionately (Gardner, Mulvey, & Shaw, 1995). Count variables are problematic for ordinary least squares (OLS) for two reasons (Gardner, et al., 1995). First, an OLS model would produce incorrect estimates because the data would violate the assumption of homoscedasticity. Second, OLS is a linear model that assumes a normal distribution of error terms. Therefore, OLS is unlikely to be a good model fit for rare-event count data.

In a Poisson distribution by definition, the mean and variance are roughly equal (Bulmer, 1967; Mears & Bhati, 2006). In addition, the Poisson distribution implies a "memoryless process" whereby events within the data are not correlated (Gardner, et al., 1995). In other words, the occurrence of earlier events does not impact the rate at which subsequent events occur.

Data may resemble a Poisson distribution but be overdispersed. The distribution of event counts may generally resemble the Poisson distribution, but the variance substantially exceeds the mean. This compromises model fit in the Poisson regression (Berk & MacDonald, 2008; Gardner, et al., 1995). Additionally, if the fitted mean count of the Poisson distribution (λ_i) is not the real rate for all events in the observed data, then the difference between the actual rates and λ_i will inflate residual variance (Osgood, 2000). Likewise, residual variance can be inflated if the assumption of a memoryless process is incorrect, but instead events are dependent upon previous ones. When the assumption that λ_i is the true rate of event occurrence is violated "… there is no more reason to expect that a Poisson regression will explain all of the variation in the true crime rates than to expect that an OLS regression would explain all variance other than error of measurement" (Osgood, 2000, p. 21).

When the variance exceeds the fitted Poisson distribution, an overdispersed Poisson model may be necessary to account for the differences between the observed count values and the expected values based on the general Poisson model (Osgood, 2000). Overdispersion models correct for deviance by altering standard error and *t*-values relative to the amount of dispersion (Gardner, et al., 1995), or by adding an error term to the Poisson model (Osgood, 2000). Ratios represent the factor by which the expected count of an outcome should increase or decrease based on a one unit predictor change, holding all other predictors constant.

Hypotheses

Based on Reuter and MacCoun's (1992) hypothesis, it is expected that there will be a positive relationship between the median travel distance of drug sellers and counts of violent incidents. Drug sellers without social ties to a drug market area may be more inclined to resort to violence because their distance from the market prevents them from wanting to socially invest in the community. Additionally, it would align with findings by Hipp & Perrin (2009) that distance prevents individuals from forming close social ties. If Reuter and MacCoun are correct, there should also be a correlation between the travel distances of buyers and violence. Longer distance buyers are more likely to be traveling to public markets lacking agreed upon standards about making exchanges. The absence of standards may cause conflict between buyers and sellers. It is also possible that markets with longer distance buyers are lucrative, public markets. The lucrativeness of the market may lead to violent competition among dealers in the market.

Results

Descriptives

Descriptive statistics of variables used in the model are shown in Table 17. Values described below reflect aggregate statistics across the five years. An average of 45 violent incidents occurred yearly per market (St. Dev. = 29 incidents). Boxplot analysis revealed that six drug markets with violence counts at or above 113 incidents are extreme outliers. A Winsorized form of the variable was created whereby the six extreme outliers were replaced with the nearest non-outlier in the data. Descriptive statistics shown below of the Winsorized variable are not very different from the original form. However, the variance of the Winsorized outcome is 744.93, compared to the original violence variable with a variance of 819.14.

When considering aggregate travel distance, the median for buyers within markets was about 1 mile, compared to sellers of about $4/5^{ths}$ of a mile. On average African Americans composed 55% of the residents within markets (St. Dev. = 32%). Sellers of Hispanic or Latino descent generally composed 20% of dealers over time. Although women averaged 12% of drug buyers, they were about 18% of sellers. Considering drug type, 29% of drug buying arrests were for crack cocaine, as compared to 44% for selling the same drug. Finally buyers within drug markets were on average slightly younger than sellers (30 versus 34, respectively).

Pearson bivariate correlations suggested potential problems with collinearity. Visual examination of the correlation matrices revealed a strong negative correlation (r = -0.80, p < .01) between racial heterogeneity and the percent of African American residents in a neighborhood. In other words African Americans were unlikely to live in drug markets with white *and* Hispanic residents. Drug markets with a high proportion of African American residents were also unlikely to have a large proportion of drug sellers of Hispanic or Latino descent (r = -0.82, p < .01). Multicollinearity was a problem in developing statistical models. Variance inflation factor and tolerance scores for all predictors within *reported* models were less than 4 and greater than 0.4, respectively.

Table 17: Descriptive statistics

	n	Mean	St. Dev.	Median	Minimum	Maximum
Violence count	170	44.97	28.69	35.50	3.00	139.00
Violence count (Winsorized)	170	44.48	27.37	35.50	3.00	109.00
Arrestee characteristics						
Buyer distance mi.	170	1.31	1.11	0.99	0.14	6.58
Seller distance mi.	170	0.91	0.57	0.79	0.07	3.69
Hispanic sellers (%)	170	0.20	0.22	0.12	0.00	0.75
Female buyers	170	0.12	0.08	0.11	0.00	1.00
Female sellers	170	0.18	0.07	0.18	0.00	0.50
Crack cocaine buyers (%)	170	0.29	0.19	0.28	0.00	0.87
Crack Cocaine sellers (%)	170	0.44	0.27	0.43	0.00	1.00
Age (buyers)	170	30.32	3.96	30.16	18.50	43.93
Age (sellers)	170	33.57	3.92	33.10	24.20	46.57
Residential composition						
Family structure	170	-0.05	0.42	-0.01	-0.94	0.80
Heterogeneity	170	0.31	0.20	0.34	0.02	0.69
Stability	170	-0.23	0.46	-0.24	-1.02	0.76
Socioeconomic status	170	-0.77	0.31	-0.76	-1.43	-0.22
African American resid. (%)	170	0.55	0.32	0.47	0.06	0.99
Area mi^2	170	0.08	0.03	0.07	0.02	0.16
Population (exposure)	170	859.21	373.14	749.23	292.49	1879.13

N=170 repeated measures of 34 drug markets.

HLM models

ANOVA

A generalized HLM for an overdispersed Poisson distribution ANOVA with no predictors was run on the violent count outcome. Results revealed significant variation in violence across markets (Table 18). The reliability estimate (.97) suggested strong year-to-year consistency within markets and sizeable differences across markets. The intraclass correlation revealed that 18% of variance was located at the market level.

Table 18: ANOVA of violent incident counts

Fixed	**β**	**ERR**	
Average annual market violence count	1.90	6.65	
Random	**σ^2**	**χ^2**	
Between market variation	0.39	1611.30	***
Within markets (over time) remaining variation	1.80		
Reliability	0.97		
Intraclass correlation	0.18		

Notes: N=169. *Df=33.* *** p <.001. ERR – Event rate ratio. Exposure variable (population) transformed using the natural log.

Models with predictors

The natural log of the residential population within each drug market was used as an exposure variable to account for differences among drug markets in the opportunity for violence to take place. Two sets of parallel models (buyer and seller distances) were used to examine the distance → within-market violence relationship. Repeated modeling of the violence outcome variable may increase the likelihood of Type 1 error. This threat to statistical conclusion validity was addressed by reducing the acceptable alpha level for all coefficients in the following models from $p < .05$ to $p < .025$ (Shadish, Cook, & Campbell, 2002).

Model 1 of Table 19 displays Poisson models examining impacts of buyer travel distance on drug market violence. Betas and event-rate ratios (ERR) for the yearly dummy variables reveal that violence in later years was significantly less than 2006 levels (-11% in 2007, -19% in 2009, and -20% in 2010). Every one unit increase in the median natural log buyer distance was associated with an expected violence count 8%

larger (*p* <.01). These findings held when controlling for buyer composition in terms of gender, ethnicity, age, and the proportion of crack cocaine purchases.

Table 19: Poisson HLM predicting violence using buyer travel distance (Models 1 and 2)

	Model 1					Model 2				
	β		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	2.01		0.11	7.50		2.04		0.13	7.66	
Time-varying covariates										
2007	-0.12	**	0.04	0.89	-2.73	-0.12	**	0.04	0.89	-2.69
2008	-0.10	†	0.04	0.91	-2.25	-0.10	†	0.05	0.90	-2.22
2009	-0.21	***	0.05	0.81	-4.52	-0.22	***	0.05	0.81	-4.43
2010	-0.22	***	0.05	0.80	-4.69	-0.23	***	0.05	0.80	-4.59
Distance	0.08	**	0.03	1.08	2.64	0.07	*	0.03	1.08	2.37
Female (%)						-0.05		0.22	0.95	-0.22
Hispanic buyers (%)						-0.07		0.17	0.93	-0.43
Age (Mean)						0.01		0.01	1.00	0.90
Crack cocaine (%)						0.01		0.12	1.01	0.08
Level 1 σ	1.54					1.57				
Level 2 σ	0.38					0.39				
χ^2	1781.33	***				1788.65	***			

Notes: N=169. † $p < .03$, * $p < .025$, ** $p < .01$, *** $p < .001$. ERR – Event rate ratio. Distance and population (exposure variable) transformed using the natural log.

Model 3 in Table 20 added in the effects of community demographic variables. Except for racial composition, no significant links with violence across markets surface. The addition of the above demographic variables rendered the buyer distance predictor marginally significant (*p* < .30).

Model 4 considers the effect of community racial composition. No significant link with violent crime surfaces. The buyer distance predictor is once again significant (*p* <.01).

Table 20: Poisson HLM predicting violence using buyer travel distance (Models 3 and 4)

	Model 3					Model 4				
	B		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	1.64		0.35	5.17		1.95		0.20	7.02	
Time-varying covariates										
2007	-0.13	**	0.04	0.88	-2.90	-0.12	**	0.04	0.89	-2.74
2008	-0.10	*	0.04	0.90	-2.35	-0.10	*	0.05	0.90	-2.28
2009	-0.22	***	0.05	0.80	-4.58	-0.22	***	0.05	0.80	-4.51
2010	-0.23	***	0.05	0.79	-4.70	-0.22	***	0.05	0.80	-4.40
Distance	0.07	†	0.03	1.07	2.25	0.08	**	0.03	1.08	2.60
Female (%)	0.02		0.22	1.03	0.12	-0.03		0.22	0.97	-0.16
African American (%)						0.15		0.27	1.16	0.56
Age (Mean)	0.00		0.01	1.00	0.66	0.01		0.01	1.01	0.92
Crack cocaine (%)	0.06		0.12	1.06	0.50	0.01		0.12	1.01	0.09
Family structure	-0.02		0.31	0.98	-0.05					
Stability	-0.24		0.27	0.78	-0.92					
Socioeconomic status	-0.71		0.39	0.49	-1.81					
Heterogeneity	-0.82		0.43	0.44	-1.92					
Level 1 σ	1.49					1.55				
Level 2 σ	0.42					0.41				
χ^2	1730.20	***				1985.66	**			

Notes: N=169. † *p* < .03, * *p* < .025, ** *p* < .01, *** *p* < .001. ERR – Event rate ratio. Distance and population (exposure variable) transformed using the natural log.

Turning to the impact of seller travel distance on market violence, Model 1 in Table 21 also reveals a positive relationship. For every one unit increase in seller median travel distance, the expected violence count increases by 11% (ERR = 1.11, p <.01). Adding of gender, ethnicity, and age composition of buyers does not reduce the effect of seller travel distance (Table 21, Model 2).

Model 2 also considers the effect of the proportion of drug sales arrests for crack cocaine. Violent crime counts are expected to be 34% higher (ERR = 1.34, $p < .05$) in markets that sell only crack cocaine compared to markets where cocaine is not sold at all.

Table 21: Poisson HLM predicting violence using seller travel distance (Models 1 and 2)

	Model 1					Model 2				
	β		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	1.99		0.11	7.35		1.91		0.15	6.75	
2007	-0.11	*	0.04	0.90	-2.44	-0.10	*	0.04	0.90	-2.33
2008	-0.08		0.04	0.92	-1.92	-0.06		0.05	0.94	-1.43
2009	-0.16	***	0.04	0.85	-3.67	-0.12	*	0.05	0.88	-2.56
2010	-0.19	***	0.04	0.83	-4.23	-0.16	**	0.05	0.85	-3.16
Distance	0.11	**	0.03	1.11	3.16	0.10	**	0.04	1.11	2.96
Female (%)						-0.32		0.24	0.73	-1.33
Hispanic sellers (%)						0.02		0.23	1.02	0.07
Age (Mean)						0.00		0.01	1.00	-0.25
Crack cocaine (%)						0.29	*	0.122	1.337	2.38
Level 1 σ	1.51					1.48				
Level 2 σ	0.39					0.41				
χ^2	1845.67	***				2000.51	***			

Notes: N=169. * $p < .025$, ** $p < .01$, *** $p < .001$. ERR – Event rate ratio. Distance and population (exposure variable) transformed using the natural log.

Model 3 in Table 22 considers the impact of crack cocaine sales as well as community demographics, except for racial composition. As neighborhoods hosting markets become more racially and ethnically diverse, lower violence counts are expected (ERR = .40, $p < .05$). The impact of seller travel distance still holds compared to earlier models. Model 4 shows no impact of community racial composition.

Table 22: Poisson HLM predicting violence using seller travel distance (Models 3 and 4)

	Model 3					Model 4				
	β		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	1.53		0.36	4.64		1.88		0.20	6.57	
Time-varying covariates										
2007	-0.11	**	0.04	0.89	-2.77	-0.10	*	0.04	0.90	-2.43
2008	-0.07		0.04	0.93	-1.72	-0.06		0.04	0.94	-1.46
2009	-0.14	**	0.05	0.87	-2.94	-0.13	**	0.05	0.88	-2.62
2010	-0.18	***	0.05	0.84	-3.61	-0.16	**	0.05	0.86	-3.13
Distance	0.09	*	0.04	1.10	2.57	0.10	**	0.03	1.11	2.95
Female (%)	-0.30		0.24	0.74	-1.29	-0.30		0.24	0.74	-1.28
African American (%)						0.07		0.27	1.07	0.25
Age (Mean)	0.00		0.01	1.00	-0.15	0.00		0.01	1.00	-0.24
Crack cocaine (%)	0.34	**	0.12	1.40	2.86	0.27	*	0.12	1.33	2.48
Family status	0.04		0.32	1.04	0.14					
Stability	-0.26		0.27	0.77	-0.95					
Socioeconomic status	-0.76		0.40	0.47	-1.89					
Heterogeneity	-0.92	*	0.42	0.40	-2.21					
Level 1 σ	1.38					1.46				
Level 2 σ	0.44					0.42				
χ^2	1947.25	***				2155.32	***			

Notes: N=169. * $p < .025$, ** $p < .01$, *** $p < .001$. ERR – Event rate ratio. Distance and population (exposure variable) transformed using the natural log.

Discussion

The primary goal of this chapter was to assess the unique impacts of drug seller and drug buyer travel distances on violent crime, using parallel time-varying overdispersed Poisson hierarchical linear models. Although recent research has investigated the relationships between drug crime and violence (Berg & Rengifo, 2009; Lum, 2011; Martínez, et al., 2008) none to date has empirically tested whether the travel distances of drug offenders may contribute to the drugs-violence nexus. This is a significant omission considering that Reuter and MacCoun (1992) allude to the idea that distance explains the social ties that drug offenders have with one another. And arguably these links are important for understanding why some drug markets are more violent than others. A number of salient findings merit further discussion.

Violence within drug markets

Results suggest that drug offender distance may be a salient factor for understanding the violence that occurs within and around outdoor drug markets. The bottom 10 of this study's 34 drug markets had less than 10 violent incidents per year. Furthermore, markets scoring below the 25th percentile had no more than 24 violent incidents each. Thus this research too reinforces the well-known principle that some places are more violent than others and adds that distance links are partially responsible for within-market violence differentials. In sum, drug markets with the longest aggregate travel distances tend to be more violent than those of shorter travel distances.

Drug buyer versus seller distance relationships with market violence

In support of Reuter and MacCoun's theoretical arguments, models revealed higher violent crime in markets where drug buyers and sellers come from farther away. Controlling for yearly differences, expected violent crime counts increase by 8% for every one unit increase in median buyer travel distance and 11% for every one unit increase in median seller travel distance. These differences in event rate ratios (and more importantly beta coefficients) within parallel models *may* suggest that different processes explain the unique relationships between drug buyer travel distances and market violence and drug seller travel distances and market violence. Furthermore, using the adjusted alpha level, seller distance is a significant predictor of market violence across all models, while buyer distance is significant in 3 out of 4 models. These findings also suggest that different causal processes may be operating. Sound conclusions regarding differential causal connections are subject to additional research on beta significant differences between buyer and seller distance models.

Also revealing, was the finding that the proportion of arrests for crack cocaine *dealing*, but not buying has a significant impact on violence. Finding that two similar yet distinct predictors have differential impacts on violent crime is interesting in its own right. For example, research by Warner and Coomer (2003) found that their community survey measure assessing the frequency of which residents witnessed drug transactions was a real predictor of community level drug trafficking rates, but not drug possession rates. In any event, this finding lends additional support to earlier research documenting the violent effects of the crack cocaine drug trade (Anderson, 1999; Blumstein, 1995; Brownstein, et al., 1995; Wilson, 1996). This finding could be attributed to systemic explanations where drug dealers are competing for profitable drug markets. Their inability to legally solve grievances may predispose them to violent conflicts, as alluded to in this research.

Limitations

Two limitations deserve mention. First, demographic contextual variables used in the analysis were interpolated across the study period using American Community Survey, decennial census, and GeoLytics data. The interpolation technique used in this research assumes a constant rate of change between time periods and may over- or underestimate values for any one specific year. As a result the error of such variables increases the farther one moves from each data collection point.

Second, areal interpolation was used to capture dynamics occurring within drug markets, considering that drug market boundaries are not coterminous with census boundaries. Census enumeration boundaries are not constructed with the boundaries of drug markets in mind, thus it is possible that interpolation of data from census values may be a misrepresentation of contextual dynamics occurring within drug markets. Again, the purpose of areal interpolation was to extract control variables that are the best estimate of dynamics likely occurring within drug market areas.

Limitations aside, there are a number of strengths to Chapter 5 of the dissertation. First, this is the first study to the author's knowledge to demonstrate a relationship between how far drug offenders travel to illicit markets and the violence that occurs within them. The strength of the relationship between drug offender travel distance and violence depends on measurements of drug purchasing versus selling. Second, this research has suggested that the systemic nature of crack cocaine selling—and not buying—has an effect on inner-city Philadelphia violence, and drug-market violence specifically. Implications suggest future research should investigate correlates that explain differential effects for drug buyer versus seller/violence nexus.

The following chapter adds to the work of Chapters 3-5 to address the critical question of this dissertation: Is there empirical support for Reuter and MacCoun's distance → market violence model? It addresses the gap left in this chapter as to whether simultaneous travel distances of buyers and sellers work in tandem to explain within-market violence.

CHAPTER 6:

TEST OF REUTER AND MACCOUN'S MODEL

Introduction

The pages that follow elaborate on the buyer and seller distance relationship in two ways. First, they investigate whether the simultaneous consideration of buyer and seller distance accounts for variation in market violence. Second, they provide a methodology for considering buyers and sellers jointly by organizing markets by distance according to Reuter and MacCoun's (1992) typology.

This chapter operationalizes Reuter and MacCoun's (1992) typology of drug markets and examines how types correlate with violence. Details of their typology can be found in the literature review but are briefly revisited below. Local drug markets are characterized by transactions occurring between buyers and sellers who live in close proximity or within the same neighborhood as the market. Export drug markets are those in which sellers from the host community deal to buyers traveling from outside the community. In import markets, the sellers travel to other neighborhoods to sell yet the buyers are local. Finally, public markets are those in which neither buyers nor sellers are from the immediate area of the drug market. Reuter and MacCoun (1992) expect import markets to be the most violent and local markets to be the least violent.

Although Chapter 5 of the dissertation does not simultaneously consider how the mixing of buyers and sellers from varying distances correlate with violence, it does show via separate models that as the travel distances of buyers *and* sellers increase there is credible reason to expect violence will increase as well. With these findings in mind—

and contrary to Reuter and MacCoun's expectations—it is expected that public markets will be the most violent out of the four. Nonetheless, import, and export markets are also expected to be associated with higher violence counts than local markets considering the lengthier travel patterns of their offenders.

Finding that public markets are the most violent would suggest opportunities for refining Reuter and MacCoun's theory. For example, the very land use factors described by the Reuter and MacCoun could be more significant than originally thought with implications for place management. Place management in public areas may be conducive to drug offending *and* violence due to the fact that public areas such as transit nodes are likely to have peak and off-peak hours of foot traffic, and in turn peak and off-peak hours of informal and formal guardians. Furthermore, the current research may be able to incorporate the above theoretical constructs with other sociological phenomena that have been known to correlate with crime. Much of the research demonstrated in the literature review has demonstrated how community level demographics can correlate not only with the presence of drug markets, but also the violence they are believed to engender. Thus it is necessary to determine if certain drug market types add any predictive ability for violence *above* what is currently known.

Reuter and MacCoun provided little attention to questions of how to operationalize their key ideas. The ability of multiple operationalizations of Reuter and MacCoun's concepts to present uniform relationships would not only serve to qualify the theory, but also address threats to validity. In sum, three research questions structure the current chapter:

1. When markets are organized according to Reuter and MacCoun's typology are there differences in violence levels by type, as predicted?
2. If expected links surface, do community demographics such as race, socioeconomic status, and stability undermine the significance of the drug market type → violent crime connection?
3. Considering the vague description of market types, can alternative operationalizations of Reuter and MacCoun's typology demonstrate convergent validity?

Methods

Variables

The final part of the dissertation utilizes the same time-varying covariates described in Chapter 5 to predict violent crime counts. Additional key predictors include those that capture Reuter and MacCoun's (1992) local, import, export, and public drug markets. Unfortunately, Reuter and MacCoun do not suggest how to operationalize a local drug market, or define what it means to be a local or regional drug offender. Prior research by Pettiway (1995) defined neighborhood drug purchases as those that took place within ½ mile of the buyer's residence. However, Pettiway's threshold selection lacked a detailed justification or rationale. It also does not take into consideration the distances buyers *and* sellers travel to drug markets.

Relying on Reuter and MacCoun's central idea about variation in the degree of local versus nonlocal mixing of buyers and sellers, interquartile range (IQR) scores were used to classify markets into types. The IQR spans cases in a sample that when ordered fall between the 25^{th} and 75^{th} percentiles, known as the middle 50% of cases (Field, 2005). The difference between the highest and lowest observations of the IQR is the IQR score. IQR scores were computed separately for the travel distances of drug buyers and sellers for each drug market, for each year of the study. A smaller IQR score would indicate that the travel distance of buyers (or sellers) within a market are more clustered around the median travel distance. Larger scores would indicate that travel distance is more dispersed around the median travel distance.

IQR scores were used to characterize drug markets according to Reuter and MacCoun's typology of drug market violence. Local markets, therefore, are cases in which the IQR score for buyers is smaller than the median IQR score across all markets for buyers *and* the IQR score for sellers is smaller than the median IQR across all markets. Import markets are those where the IQR for buyers is less than the median and the IQR score for sellers is greater than the median IQR. Export markets are characterized by an IQR score for buyers that is greater than the median, but less than the median for sellers. Public markets are those where the IQR scores for buyers and sellers are greater than their medians.

Three dummy variables indicated a market's categorization for each of the five years of the study (Import = 1, else = 0; Export = 1, else = 0; and Public = 1; else = 0). Local markets were included in the reference string. This operationalization allows assessing how each drug market category correlates with violence over time. Time is measured in Chapter 5.

Analytic focus

1. Are there significant violent crime count differences across among Reuter and MacCoun's (1995) four drug market typologies?

2. If so, are their predictions about the ordering of violence by type correct? If their typology is correct the following analysis will find import markets the most violent (although models from Chapter 5 provide some contrary results). Local markets also should be the least violent.

The types of models run here—generalized HLMs for overdispersed Poisson-distributed count outcomes with years nested within markets—are the same as seen in Chapter 5.

Results

A total of 169 repeated (time-varying) measurements of 34 drug markets were included in the results described below. The drug market typology operationalization described above reveals that 32% of all market-years are local, 17% - export, 18% - import, and 33% - public.[23]

In light of multicollinearity checks it was necessary to construct models with predictors grouped as follows:

1. Family structure, socioeconomic status, stability, percent African American, and percent of the population aged 10-24;
2. Socioeconomic status, stability, and percent African American
3. Family structure, socioeconomic status, and stability.

Conditional models begin with assessing the influence of time and Reuter and MacCoun's four market types on violence. In Model 1 of Table 23 the reference category includes local drug markets in 2006. Each unique year from 2007 to 2010 had

[23] See Chapter 5 for descriptives of additional variables used in this analysis.

lower expected violent crime counts compared to 2006, controlling for market types. Specifically, event rate ratios reveal that expected violence counts were 11% lower in 2007 (p <.01), 9% lower in 2008 (p <.05), 18% lower in 2009 (p < .001), and 21% lower in 2010 (p <.001) than 2006 levels. This temporal trend will have implications for the interpretations of additional coefficients in the model.

Turning to drug market types, markets in which buyers and sellers come from more distant areas—public markets—are expected to have violent crime counts that are 14% higher (ERR= 1.14, p <.05) than local drug markets. This holds controlling for temporal variation, and across alternative market types. Import markets—those in which dealers are mostly outsiders and buyers are mostly residents—and export markets—those in which dealers are mostly residents but buyers are mostly outsiders—have expected violent crime counts similar to local drug markets. Import markets' expected counts (ERR = 1.03) are the most similar to local markets. This is contrary to Reuter and MacCoun's predictions.

Model 2 (Table 23) adds in community level indicators created using 2000 census and postcensal data as described in Chapter 5. Family structure, socioeconomic status, stability, and the percentage of African American residents are added. The effect of public markets on violent crime remains significant. This market type remains important, net of community fabric.

Socioeconomic status matters. For every 1 unit increase in status, violence is expected to decrease by 59% (ERR = 0.41, p < .05). This is the first study to the author's knowledge to find an impact of socioeconomic status on drug market violence, after controlling for a distance-based market typology.

Table 23: Poisson HLM using IQR typologies to predict violence counts (Models 1 and 2)

	Model 1					Model 2				
	β		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	1.96		0.11	7.10		1.57		1.05	4.83	
Time-varying covariates										
2007	-0.12	**	0.04	0.89	-2.614	-0.11	**	0.04	0.89	-2.61
2008	-0.10	*	0.04	0.91	-2.26	-0.10	*	0.04	0.91	-2.21
2009	-0.20	***	0.05	0.82	-4.39	-0.20	***	0.05	0.82	-4.26
2010	-0.23	***	0.05	0.79	-4.77	-0.20	***	0.05	0.82	-4.11
Import	0.03		0.05	1.03	0.62	0.02		0.05	1.02	0.46
Export	0.06		0.05	1.06	1.14	0.06		0.05	1.06	1.17
Public	0.13	*	0.06	1.14	2.31	0.12	*	0.05	1.12	2.12
Family structure						0.15		0.35	1.16	0.42
SES						-0.89	*	0.42	0.41	-2.10
Stability						-0.27		0.27	0.76	-1.02
African American (%)						0.56		0.35	1.75	1.60
Pop. 10-24 (%)						-2.56		4.17	0.08	-0.61
Level 1 σ	1.56					1.53				
Level 2 σ	0.39					0.38				
χ^2	1778.57	***				1535.01	***			

Notes: N=169. * $p < .05$, ** $p < .01$, *** $p < .001$. ERR – Event rate ratio. Exposure variable (population) transformed using the natural log.

Alternative community-level demographics are considered in Model 3 (Table 24) including socioeconomic status, stability, and the percentage of African Americans residing in a drug market area, excluding family structure and heterogeneity. Socioeconomic status maintains a significant, albeit dampened effect, with 1 unit increases in the predictor associated with 53% decreases in violence. The public market variable remains significant. Public markets are expected to have 12% higher violent crime counts (ERR=1.12, p <.05) than local drug markets. Model 4 removes the effect of race to just examine how socioeconomic status and stability impact violence. Both variables yielded non-significant effects. Yet once again, controlling for community-level demographics public markets are expected to have 12% higher violent crime counts (ERR=1.12, p <.05) than local drug markets.

Table 24: Poisson HLM using IQR typologies to predict violence counts (Models 3 and 4)

	Model 3					Model 4				
	β		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	1.02		0.39	2.77		1.37		0.31	3.92	
Time-varying covariates										
2007	-0.11	**	0.04	0.89	-2.60	-0.11	**	0.04	0.89	-2.56
2008	-0.09	*	0.04	0.91	-2.18	-0.09	*	0.04	0.91	-2.13
2009	-0.19	***	0.05	0.83	-4.30	-0.19	***	0.05	0.82	-4.22
2010	-0.20	***	0.05	0.82	-4.16	-0.22	***	0.05	0.80	-4.54
Import	0.02		0.05	1.02	0.45	0.03		0.05	1.03	0.50
Export	0.06		0.05	1.06	1.16	0.05		0.05	1.06	1.07
Public	0.11	*	0.05	1.12	2.10	0.12	*	0.06	1.12	2.06
Family structure						-0.22		0.28	0.80	-0.78
SES	-0.76	*	0.37	0.47	-2.07	-0.69		0.38	0.50	-1.81
Stability	-0.23		0.26	0.80	-0.89	-0.13		0.25	0.88	-0.51
African American (%)	0.52		0.30	1.69	1.75					
Level 1 σ	1.51					1.56				
Level 2 σ	0.38					0.39				
χ^2	1589.67	***				1422.93	***			

Notes: N=169. * p < .05, ** p < .01, *** p < .001. ERR = Event-rate ratio. Exposure variable (population) transformed using the natural log.

Alternative operationalizations

Due to the lack of information on how to define Reuter and MacCoun's drug market indicators, two alternative operationalizations were considered in this study. The first creates market types using percentile rankings. In accordance with the basic theoretical argument, local markets are those where the aggregate buyer and seller travel distances fall below the 33rd percentile. Import markets are those that score below the 33rd percentile for buyers, but above the 67th percentile for sellers. Export markets are characterized by a distance score for buyers above the 67th percentile, but less than the 33rd percentile for sellers. Public markets are those where the distance scores for buyers and sellers are above the 67th percentiles. The advantage of this approach is that the four market types capture outliers on travel distance. The four outlier market types can then be compared to the markets where the aggregate travel distances of buyers and sellers fall *between* the 33rd and 67th percentiles. In sum, the purpose of the percentile operationalization was to capture markets characterized by extreme aggregate travel patterns and compare them to markets characterized by more typical travel distances.

The second alternative operationalization used buyer and seller level medians to distinguish between generally within-own-neighborhood offending versus drug offending occurring outside of one's neighborhood. In this case local markets are those in which the aggregate buyer and seller travel distances fall below respective medians across all markets. Import markets are those that fall below the median for buyers, but above the median for sellers. Export markets are characterized by a median distance score for buyers that is greater than the overall median, but less than the overall median for sellers. Public markets are those where the median distance scores for buyers and sellers are above their respective overall medians.

Table 25 provides information on the convergent validity of the alternative operationalizations with the original that used inter-quartile range distance scores. The proportions in the table correspond to the percentage of markets in for a given type within a given year, that were characterized by the same or an alternative type. In 2006, eighteen clusters were classified as local markets using the inter-quartile range score method. Reading across the row one can see that 44% and 72% of markets were classified the same way using the percentile and median operationalizations, respectively. These same-type classification percentages were the largest in this year for this market type. Across additional years in the study period the median approach converged more closely than did the percentile with the IQR approach. Convergence differences with the IQR method are substantially reduced when looking at the years 2007-2008.

Turning to import markets, it appears that the median operationalization better matches the IQR method than does the percentile approach from 2006-2009. For 2010, both operationalizations failed to correctly classify the one market originally classified as local. Convergent validity appears to be the worst for export markets. For 2006, the percentile approach was unable to classify any of the original export markets. The median approach was just as likely to classify an originally determined export market as an export market, as it was to classify it as a public market. And for 2007, neither approach demonstrated convergence. In the case of public markets, both alternative operationalizations demonstrated good convergent validity, yet across all years the median approach outperformed the percentile method. In sum, classifications appear to be the most similar for public markets, less similar local markets, and the least similar for import and export markets.

Table 25: Convergent validity

Year	IQR score Type	N	Percentiles Local	Import	Export	Public	Median Local	Import	Export	Public
2006	Local	(18)	.44	.06	.00	.00	.72	.11	.06	.11
	Import	(6)	.17	.17	.00	.00	.17	.67	.00	.17
	Export	(2)	.00	.00	.00	.00	.00	.00	.50	.50
	Public	(8)	.00	.00	.00	.50	.00	.13	.13	.75
2007	Local	(11)	.18	.00	.09	.00	.73	.00	.27	.00
	Import	(8)	.13	.13	.00	.25	.13	.38	.00	.50
	Export	(5)	.20	.20	.00	.00	.40	.40	.00	.20
	Public	(10)	.00	.00	.10	.40	.30	.00	.10	.60
2008	Local	(13)	.54	.00	.00	.00	.69	.08	.08	.15
	Import	(6)	.00	.33	.00	.00	.17	.50	.00	.33
	Export	(5)	.00	.00	.20	.00	.40	.00	.60	.00
	Public	(10)	.00	.00	.00	.70	.00	.10	.00	.90
2009	Local	(7)	.29	.00	.14	.00	.43	.00	.57	.00
	Import	(9)	.00	.22	.11	.00	.22	.44	.11	.22
	Export	(8)	.38	.00	.13	.00	.63	.13	.25	.00
	Public	(10)	.00	.00	.00	.50	.00	.00	.00	1.00
2010	Local	(7)	.14	.00	.00	.00	.57	.00	.29	.14
	Import	(1)	1.00	.00	.00	.00	1.00	.00	.00	.00
	Export	(8)	.25	.00	.38	.00	.25	.00	.63	.13
	Public	(17)	.12	.18	.00	.41	.12	.24	.12	.53

Note: IQR - Interquartile range. Values in parentheses reflect the number of markets within each type.

Parallel Poisson hierarchical models were used to determine if the alternative operationalizations provide results substantially different from those of the original IQR typology. Using the percentile approach (see Appendix F), models reveal that none of the market types has a significant impact on within-drug market violence. These findings hold when controlling for demographic factors such as race, status, stability, and the percentage of residents between the ages of 10 and 24.

When considering the median operationalization approach, findings appear to be more in line with those of the original typology. This is not surprising, however, considering that Table 25 shows good convergent validity between the IQR and median measures. Appendix G models use the market typology created through the median operationalization. Model 1 indicates that public drug markets are expected to have violent crime counts that are 14% higher than local drug markets, controlling for changes over time and other market types. The results of the current model reflect those of the parallel Model 1 in Table 22 and Table 23. Models 2-4 practically mimic the findings of the original models in Table 23 with two key exceptions. First, in the median operationalizations the impact of the public market predictor on violence shifts to marginal significance. Second, socioeconomic status achieves marginal significance at the .07 level compared to the original Model 4 in Table 23. In sum, in two out of three operationalizations there is partial and consistent support for the Reuter and MacCoun model

Discussion

This chapter presents the full test of Reuter and MacCoun's theory of how the travel distances of drug offenders covary with violence within drug markets. Time-varying dummy-coded predictors of seller and buyer distance inter-quartile range scores capturing local, import, export, and public markets were used in an overdispersed Poisson hierarchical linear model predicting violent crime counts. Briefly, Reuter and MacCoun expected that local markets would be the least violent, followed by export, public, and import—the most violent of all. Results provided partial support for Reuter and MacCoun's theory with perhaps an opportunity to revise the expected violence rankings.

Market typology and theoretical implications

Contrary to the expectations of Reuter and MacCoun, public markets in which buyers and sellers travel from greater distances are the only ones expected to have violent crime levels significantly different from the safest drug markets (local). Even when controlling for a host of community level dynamics, public market violence counts are generally 12% higher than the least violent drug markets. In partial support for the theory, public drug markets do reveal themselves as comparatively high violent crime areas.

Turning to the implications of findings for theoretical concerns, this research suggests that there may be only two typologies of drug markets in Philadelphia that matter for explaining violence. These would include local markets in which both buyers and sellers travel shorter distances, originating their travel closer to the market neighborhood, and public markets with drug dealers and buyers coming from farther away. Whereas local markets may be those in which neighborhood patrons and entrepreneurs compose the market and have established real neighborly connections, public markets could be the most extreme cases with both groups from socially *and* spatially distant communities. It's possible that such distance could be responsible for each group's naïveté about the drug market location of which transactions occur *and* the conflict that arises as each group is less likely to understand how to make exchanges in a covert manner. Research on a heroin drug market in Los Angeles' MacArthur Park indicates that ”go-betweens” frequently worked as mediators between drug dealers and buyers circling around the park by vehicle to facilitate exchanges (Boyle & Anglin, 1993). The ”go-betweens” in this public market worked almost as language translators for both parties by reducing misunderstanding, conflict, and possibly violence. Indeed, research suggests that MacArther Park "… was seen as friendlier and not as cutthroat as [Skid Row] downtown" (Boyle & Anglin, 1993, p. 163).

The historical evolution of the city of Philadelphia may also be instrumental in explaining violence within drug markets. The spatial growth of Philadelphia to its present form of 134 miles didn't occur in an incremental fashion. The city of Philadelphia was at one time a small area (within the county of Philadelphia) that encompassed much of what's now known as Center City (Historical Society of Pennsylvania, 2012). In 1954 the city annexed the remaining land in the county of Philadelphia, which included neighborhoods such as Southwark and Moyamensing—hence the frequent colloquialism used to characterize Philadelphia as a "city of neighborhoods." Or more aptly put, the city may really be a city of small cities or townships. Such historical factors may have implications for the extent to which the offending populations identify with neighborhoods as safe-havens for illicit activity. Empirical results from this study revealed that local drug markets were the least violent, but export and import markets (those in which the aggregate travel distance of buyers *or* sellers was reflective of short, possibly within-neighborhood travel patterns) experience violence levels not significantly different from local markets. Thus it is possible—but not empirically explored here—that having one drug offender in a transaction (buyer or seller) from the host neighborhood may translate into perceived and real safety for the local offender. The traveling offender may experience fear from not residing in the local area and having fewer (if any) social ties. They may choose to engage in behavior to avoid violence considering that they are outside of their own neighborhood where they could quickly solicit support from peers if the transaction turns for the worst.

When considering public markets, findings lend some support to Reuter and MacCoun's hypothesis that they are more likely to be located around land uses that attract large numbers of people. This was exemplified by the public market that was located in and around the Greater Broad and Olney area. The Olney Transportation Center, located at the intersection of Broad and Olney Streets attracts many people because it serves as a major subway and bus transit node. In addition, a number of retail stores align Broad Street in the area, which renders it a mini commercial district. The stores, however, generally close by 6 p.m. in the evenings leaving very little guardianship in the area. Residential dwellings are located on side streets just outside of the market area, which limits capable guardianship during these hours. The remaining public markets were located around the area of Philadelphia historically known as the Badlands. These public markets as well were located at and near the Market-Frankford elevated train line in the lower Northeast section of Philadelphia. At the same time, however, local, import, and export markets can be also be found near major transit nodes in the city as shown in Appendix H. Major transit nodes tend to cluster near land uses such as commercial districts that attract many people. This suggests that although public markets are significantly more violent than the other types, they are not the only ones to operate in "public" areas.

Limitations and strengths

This study is not without its limitations. First, Reuter and MacCoun's typology alludes to other concepts distinguishing drug markets besides travel distance. Namely, they argue that different economic patterns can be seen for each typology of drug market and that for certain drug markets the flow of cash is within the neighborhood versus outside of the neighborhood, depending of the residency of drug buyers and sellers. This research does not consider those factors. Such an inquiry will have to wait for qualitative research. Additionally, the operationalization of local, import, export, and public drug markets used in this study is only one approach of many that could be employed. A different operationalization of concepts may alter the relationships seen in this research.

Second, drug market indicators served as five annual observations of thirty-four markets outlined in Chapter 3 of the dissertation. Some of the drug markets changed classifications for some of the years in the study period. It is possible that drug markets used in this study are more dynamic or stable than operationalized here. For example, ten 6-month observations would have allowed for the measurement of additional variation with drug markets being able to change from one typology to another on a 6-month basis rather than a yearly basis. Shorter, 6-month observations however, may be unduly influenced by a few long distance travels, whereas such outliers would have less of an influence on the data of a longer time frame.

The existence of these limitations does not substantially undermine the study. Several strengths exist. First, to the author's knowledge this is the first study to test Reuter and MacCoun's theory of drug market violence. No other study to date has examined the possibility that drug markets can be conceptualized by the mixing of participants from varying travel distances, nor have they demonstrated that such conceptualizations connect to systemic drug market violence. Second, although the proper time-unit of analysis is yet to be determined this is the first study to the author's knowledge to assume and control for the possibility that a drug market's type may change over time. The assumption of temporal stability may or may not be a good one. Results suggest that urban structure continues to play a major role in the occurrence of drug market violence, and market dynamics are instrumental in understanding the drugs/violence connection.

CHAPTER 7:

CONCLUSION

This dissertation contributes to a growing body of research exploring the connection between drug markets and violent crime. Results of this study suggest that it is possible to categorize drug markets based on the varying travel distances of their participants to understand the levels of violence that take place within them. No study to the author's knowledge has addressed this inquiry, using data from a large city such as Philadelphia. Furthermore, this research may possibly be the first test of the Reuter and MacCoun's typology. Finding partial support for this market typology, there are significant implications for theory development, policing and public policy, and future research.

Four layers compose this research. The first is an exercise to spatially outline Philadelphia drug markets using nearest neighbor hierarchical clustering. The second investigates and compares models explaining the travel distances of drug offenders arrested in the aforementioned drug markets. The third layer considers whether aggregate travel distance correlates with within-drug market violence. The final layer tests whether a categorized, theoretically driven operationalization of distance drives violence within drug market areas. Implications provided below focus mainly on the final layer, which is the focus of this dissertation. The key dissertation findings are:

1. Travel distances of buyers and sellers vary by individual demographic characteristics, and drug type.

2. Controlling for race, family structure, status, and heterogeneity, as the aggregate travel distance of buyers and sellers increases, so too does market violence.
3. Markets dominated by the sale of crack cocaine are significantly more violent (40%) than those where crack cocaine is not available.
4. Public markets (those in which buyers and sellers travel from outside the neighborhood) are the most violent out of the four.
5. Violence levels in export and import markets are not significantly different from local markets.

Implications for theory

Reuter and MacCoun

This research serves as a partial test of Reuter and MacCoun's typology of drug markets. This research has provided empirical support for the existence of two types of drug markets. These include less violent local drug markets composed of drug offenders from the drug market community, and significantly more violent public markets with drug offenders that travel longer distances. A number of control variables were used throughout analyses in this dissertation. Unfortunately, the possibility of mediating and moderating relationships was beyond the scope of this dissertation.

Reuter and MacCoun provide a useful typology that explains violence levels in different drug market types. Related research has explored drug delivery styles (Curtis & Wendel, 2007), how race and ethnicity works in drug dealing networks and organizations (Murji, 2007), and drug market environmental features (St. Jean, 2007). Reuter and

MacCoun's theoretical contribution is the hypothesized connection between drug offender travel distance and violence. Partial tests of their theory shown in this dissertation provide some support in that the mixing of buyers and sellers from distant residences has implications for violence. Although this research shows that import markets are *not* in fact the most violent markets (public markets were revealed as most violent), the finding that buyer-seller interactions as measured by distance matter lends support to Reuter and MacCoun's expectations. On the other hand, models also show that the travel distances of buyers and sellers *independently* contribute to violence levels in drug markets. Therefore, this dissertation has shown that there are independent (separate buyer and seller) impacts as well as interactive (buyer and sellers together) impacts on violent crime. Conversely, it could be argued that interactive impacts are actually additive. Recall that *separate* buyer and seller models from Chapter 5 reveal markets are the most violent when each group travels long distances. Thus it may be of no surprise that public markets—which group long distance buyers and long distance sellers—are the most violent. They contain the worst of both worlds. Unfortunately, the pathway by which distance operates is unclear. Possibilities are explored in further detail below.

Although central to the theory is the idea distance typology links to within-drug market violence, a latent idea is that distance is a proxy variable for social ties, which in turn correlates with market level violence. The current research was without data to examine the number and strength of social ties within the drug market area. Clearly, physical proximity to a drug market presents benefits to a drug user. Living in or around a drug market arguably increases one's exposure to and familiarity with the drug market and its participants. Such proximity may increase or decrease anxiety, but the frequency of exposure may enable one to more accurately assess threats of the drug market (e.g. police presence, drug robbers, sellers of watered down products) and also reduce the time required to carry cash and drugs to and from the market, which translates into reduced vulnerability. These reasons could be why local drug markets are less violent than public ones.

Social proximity could also provide additional explanations as to how distance correlates with violence. Research has shown that distance serves as an impediment to forming social ties between residents of the same neighborhood (Hipp & Perrin, 2009) and that social ties and capital are important for drug markets to flourish (Pattillo, 1998; St. Jean, 2007). What is less clear is whether the travel distances of drug offenders in some way explains the amount or strength of social ties in a drug market, which in turn serves to suppress or elevate crime levels. For example non-local drug dealers with less exposure to a community may find it difficult to set up a drug market in a new community controlled by other drug dealers. This lack of exposure and social ties with residents and dealers, combined with perceived encroachment, may be met with violence. Such an example would suggest that it is not the travel distance in and of itself that explains market violence, but the social ties that flow from physical proximity that explains the violence. Therefore, while distance may be a well-accepted indicator of physical proximity, it's viability as a proxy measure of social ties is at least questionable. Future research should explore this more complicated relationship to uncover the pathway by which drug offender travel distance correlates with within-drug market violence. Such an approach would build on journey to crime literature by not only drawing connections between two crime types (drug offending and violence) but also showing how social and physical distance work in tandem (or not) to explain violence levels. Indeed historical accounts demonstrate the significance of neighborhood identity in Philadelphia, which may be suggestive of the social ties of local offenders, and perceived and actual safety benefits that flow from offending in one's own neighborhood.

Journey to crime

Although not primary purpose of this dissertation, this is the first research to examine not only the travel journeys of drug buyers but also drug sellers using hierarchical models. Furthermore, it compares the travel journeys to drug sellers and buyers finding that different processes *might* explain the respective Poisson distance distributions. Hopefully, this research will open the door for additional research examining individual-level travel decisions by drug buyers and sellers. Some of these decisions could include mode of transportation. Constraints suggest that walkers are more likely to patron local markets than public markets, yet such an inquiry will have to wait for future research.

Additional research on drug offending journeys to crime (and journey to crime research overall) should seek to refine operationalization of the criminal journey. Although research has demonstrated that most drug offenders (like other offenders) offend close to home, the criminal journey is arguably unlikely to be a direct trip from home to the arrest location. For example, drug buyers may travel from home to a drug treatment center across the city. From there they may stop by a nearby outdoor drug market that exploits the proximity of the drug treatment center. The above example would undermine the idea of a public market (composed of distant sellers and distant buyers as determined by identification). Having each drug offender's last location prior to arrest would be helpful for addressing this problem. Although such data are not recorded by official arrest records, field experience with the Philadelphia Police Department during the summer of 2009 revealed that officers frequently inquire about where an offender traveled from prior to arrest. This knowledge could be exploited in a more structured research environment.

Systemic violence explanations

Finding that violence is higher in public markets opens the door to investigations of the types of violence occurring within drug market types. It is possible that the violence occurring within public drug markets reflects conflicts related to the illegal nature of drug markets explored in the literature review (Goldstein, 1985). Therefore, distance typologies may not only serve as explanations for violence levels but also for the *types* of violence within drug markets. If public markets are truly profitable locations where drug dealers and buyers from far distances converge to make exchanges, violent offenses within and nearby may be reflective of that. These areas may have high levels of robberies if buyers are seen as targets when approaching or leaving the market. Assaults and robberies may also be prevalent against drug sellers and used as a manner to intimidate sellers encroaching on the territory of others. Future research may consider the use of logistic regression models to explore which variables predict drug market type.

Implications for policing and public policy

Practically speaking, there is the potential to inform market interdiction and the allocation of drug intervention resources by spatially outlining drug markets.

Categorizing drug markets based on travel distance and violent crime levels may inform problem-oriented policing strategies to alleviate drug crime. Considering statistical support for the existence of two distinct types of drug markets—local and public, it is possible to argue that different policy responses are necessary for each market type. For example, in the case of low-violence local markets law enforcement may be less likely to have high levels of community support because drug offenders and law-abiding citizens are more likely to share similar social networks and less likely to report illicit activity as a result. This would suggest that socially-oriented responses rather than policing strategies may be more appropriate for local drug markets. Examples of this include drug treatment facilities to reduce demand and disrupt the drug market. However, research by Saxe et al. (2001) suggests that policymakers should be careful not to confuse local drug activity with local drug dependency. Other research by Rengert and colleagues (2000) and Robinson and Rengert (2006) and earlier work by Wilson (1996) notes that drug markets are likely to be located in and near areas of poverty. Job access may be limited in these communities, explaining why some residents have turned to drug-dealing for income. Therefore, providing job training and access to upward mobility may not only increase the employment prospects of local residents but reduce the likelihood that drug markets will be able to sustain themselves in disadvantaged neighborhoods.

In the case of public markets however, law enforcement may want to consider policies that would specifically address regional buyers, which may involve multi-jurisdictional policing efforts. The Philadelphia Police Department recognized that many drug buyers were from outside the city limits (Rengert, 1996b). To respond to the apparent regional demand of non-local buyers they initiated Operation Fishnet, which allowed the department to confiscate vehicles from non-city residents used to travel into the city to purchase drugs.

From a public health perspective, it could be the more regional sellers who are contributing to the destruction of communities via their lack of investment and willingness to resort to violence. From a geography perspective, the nature of public markets, due perhaps to their location around public spaces such as transportation centers and major intersections, suggests that land use may be important to their vitality. In a study of Wilmington (DE) drug sales, Rengert and colleagues (2000) found drug markets tended to cluster near interstate highway exits. Their findings suggest that street re-routing may be necessary to confuse non-local buyers, and make it more difficult for them to traverse from highway off-ramps to drug markets. Complicating access to drug markets may deter buyers from venturing deeper into some communities to purchase drugs. Research has shown that street re-routing is effective at preventing other crime types (Wagner, 1997).

The advent of CCTV cameras has allowed the activities occurring in such areas to be recorded for police investigations. For example, the Philadelphia Police Department has prioritized the placement of its surveillance cameras to street intersections, transit nodes, and other areas that draw large numbers of people. Thus the installation and monitoring of CCTV cameras may assist law enforcement with interdiction efforts for public drug markets as well.

The advantage of interdiction in public markets is that there may be businesses willing to work with the police. Therefore, it may be appropriate for the police to take advantage of business owner input and support through community meetings to gather intelligence. Such information could aid in the planning of police crackdowns and the targeting of specific drug sellers or selling organizations that contribute disproportionately to the violence in the community. After an initial crackdown occurs, law enforcement may want to have ongoing dialogue with business owners to determine if the drug market is expanding, contracting, and/or being displaced to other areas of the neighborhood.

It would also be appropriate to involve multiple agencies in the effort to address public markets. For example, fieldwork during the summer of 2009 with Philadelphia foot patrol officers indicated that the police would frequently contact the city Licenses & Inspections office to report derelict properties used by vagrants and drug offenders. Coordinated strategies between the police and other city agencies may be effective at removing viable places for non-local sellers to deal drugs (Mazerolle & Ransley, 2006). In a related sense, public markets would also be acceptable places to deliver specific deterrence messages through coordinated efforts of the police, prosecutor and social welfare office (Kennedy, 1998). Such programs could target non-violent drug sellers and garner the support of their families and the community such that they may shift to prosocial activity in lieu of strict prosecution.

Although literature on the drug-violence *correlation* has grown substantially, there remains little evidence of *causality*. Therefore, it would be naïve to assume that policy approaches meant to address drug crime will lead to a diffusion of benefits to violent crime as well. Recent research has shown that policing initiatives against drug crime may effectively address *drug crime* while having no real effect against violent crime (Corsaro, Brunson, & McGarrell, 2010).

General limitations

There are limitations to the methodology of this dissertation. The first includes the use of official police data to construct the drug markets. Arguably, police incident data are biased in that they only reflect incidents brought to the attention of the police, and therefore not reflective of incidents that were not reported. Research has shown that there are a number of reasons that offenses are not brought to the attention of the police, including, but not limited to victim complicity, fear of retaliation, and the possibility that certain incidents are better handled by social services rather than the police (Gottfredson & Gottfredson, 1988). Considering that this work is a policy-oriented piece intended to assist law enforcement interdiction of drug markets, the use of police data is likely ideal as the results can more easily translate into policy recommendations for the Philadelphia Police Department.

Second, it is important to recognize that this research does not draw a connection between travel distance and *drug-related* violence. This is due to the fact that incident data do not reveal whether violent incidents are the result of drug deals gone awry. Even if the Philadelphia Police Department collected such data, the exclusion of drug offenders from the protections of the criminal justice system undermines the perceived ability of drug offenders to report systemic violence (Black, 1976). In spite of this, results suggest that there is a real relationship between travel distance and within-drug market violence. Whether or not travel distance correlates with *drug-related* market violence specifically is an inquiry amenable to future qualitative research.

Third, this dissertation assumes that the drug markets are stable over time. In other words it is believed that the drug markets are not contracting or expanding spatially. This concern was addressed by using five years of data to identify ongoing drug problem areas rather than using one or two years of data that may be reflective of temporary policing initiatives. It is important to note that many of the markets changed typologies over time; however, public markets were the most stable.

Fourth, it is possible that the drug markets constructed from the nearest neighbor hierarchical clustering technique are not real, but abstractions of reality. Recent work by Taylor (2010b) argues that there are several inconsistencies that hot spot policing researchers must address before hot spot policing can advance to a national policy. Although it is not in the theoretical interest of this dissertation to address the nuances of hot spot policing at the national level, Taylor's point does bring into question the construct validity of hot spots techniques. His theoretical assertion that hotspots are characteristics of places rather than actual places is noteworthy, and partially supported by findings here. For example, the many ways to technically identify a hot spot and the lack of agreement on the appropriate context in which to use certain techniques would make the advancement of a national hot spot policing agenda premature. Analytically and methodologically this work has taken steps to address some of these concerns, and communication with the Philadelphia Police Department during the summer of 2009 has confirmed that many of the 34 drug markets outlined in this work are areas of high drug activity. It is recognized however, that police confirmation of drug markets constructed by police data does not represent an independent assessment.

Fifth, this research can only draw implications related to the travel patterns of offenders as it excludes multiple cases committed by the same offender. Although studying the nesting of trips within offenders is an interesting inquiry in its own right, it is outside of the theoretical interests of this dissertation. Furthermore, there is no way of knowing whether earlier trips to buy or sell drugs by an offender influenced their later trips.

Sixth, this research operationalizes the journey to crime as the distance from the home to arrest location. Inherent in this method is the assumption that offenders made direct trips from home to the arrest location, which may or may not be accurate. Additionally, the quantitative focus of this research and use of official police data prevents it from measuring the travel distances of homeless drug users. Nonetheless, time and time again research has shown the use of the home as the origin of travel patterns has implications for criminological theory and criminal justice practice as the likelihood of offending decreases the farther one moves from their home (Rengert, et al., 1999).

Conclusion

In spite of the above limitations there are practical implications that may extend from this work. This dissertation has tested a theoretical assertion that drug markets have varying levels of violence and that import markets are the most violent of all. Similar to large big box retailers, drug markets (especially public markets) may draw retailers (dealers) and customers (drug buyers) from more distant areas than a small convenience store (or corner drug market), which in turn has implications for violence.

Removing buyers and sellers from public drug markets may not only reduce conflict within, but also reduce the demand and supply that makes drug markets profitable. Considering that research has shown that drug and violent crime often go hand in hand (Gorman, et al., 2005), it is possible that law enforcement initiatives could lead to a diffusion of benefits and reduce violent crime as well, as evidenced from Operation Ceasefire in High Point, NC (Hunt, et al., 2008). In other words, the above implications relative to finding partial support for the typology may not directly address violent crime, but the processes that facilitate it, as implied by Reuter and MacCoun. In turn, findings from this dissertation may lend support to the argument that tailored approaches to individual drug markets are necessary. Although, superficially, many street level drug markets appear to be similar, it may be worthwhile for crime analysts to examine the travel distances of buyers and sellers and incorporate this knowledge into their crime reduction planning.

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APPENDICES

A. IRB and data security

All data are maintained in an encrypted folder to prevent unauthorized access. Encrypted folders and contents are only accessible by those with administrative rights to the account on the host computer. Access is limited solely to the host computer, by the person with administrative rights to the account of which the folder was originally saved.

The author has successfully completed the Collaborative Institutional Training Initiative (CITI) course on the protection of human research subjects.

B. Chapter 4 additional buyer models

	Model 4				Model 5			
	β		SE	*t*	β		SE	*t*
Intercept	0.65		0.81		0.10		0.89	
Individual								
Age	4.50E-03	*	2.23E-03	2.01	4.47E-03	*	2.24E-03	2.00
Female	-0.16	*	0.07	-2.22	-0.16	*	0.07	-2.21
Hispanic	-0.73	***	0.08	-9.37	-0.74	***	0.08	-9.40
White	1.17	***	0.08	15.39	1.16	***	0.08	15.18
Narcotics	0.30	**	0.10	2.96	0.30	**	0.10	2.94
Powder cocaine	0.32	**	0.11	2.99	0.31	**	0.11	2.94
Crack cocaine	-0.06		0.06	-1.00	-0.06		0.06	-0.87
Heroin	0.60	***	0.08	7.38	0.59	***	0.08	7.25
Market								
Marijuana (%)	-0.40		0.40	-1.02				
Female (%)	1.46		1.95	0.75	1.74		1.97	0.89
Age (Mean)	-0.03		0.02	-1.37	-0.02		0.03	-0.65
Narcotics (%)					0.33		1.53	0.22
Powder cocaine (%)					-0.16		1.54	-0.11
Crack cocaine (%)					-0.56		0.63	-0.89
Heroin (%)					0.39		0.41	0.95
Level 1 σ	2.89				2.89			
Level 2 σ	0.11				0.11			
χ^2	223.38	***			180.72	***		
Deviance	20250.30				20243.42			
Parameters	2.00				2.00			

Notes: N = 5,171. * p <.05, ** p <.01, *** p <.001.

	Model 6				Model 7			
	β		SE	*t*	β		SE	*t*
Intercept	-0.62		0.85		0.09		0.73	
Individual								
Age	4.48E-03	*	2.23E-03	2.00	4.50E-03	*	2.23E-03	2.02
Female	-0.16	*	0.07	-2.20	-0.16	*	0.07	0.03
Hispanic	-0.75	***	0.08	-9.53	-0.75	***	0.08	-9.48
White	1.16	***	0.08	15.04	1.15	***	0.08	15.03
Narcotics	0.29	**	0.10	2.94	0.29	**	0.10	2.94
Powder cocaine	0.31	**	0.11	2.91	0.31	**	0.11	2.91
Crack cocaine	-0.06		0.06	-0.98	-0.06		0.06	-0.98
Heroin	0.60	***	0.08	7.37	0.60	***	0.08	7.32
Market								
Female (%)	1.52		1.93	0.79	1.15		1.88	0.61
Age (Mean)	0.00		0.03	-0.07	-0.01		0.03	-0.39
Hispanic (%)	0.80		0.45	1.79				
White (%)	0.12		0.43	0.27				
African American (%)					-0.43	†	0.23	-1.89
Level 1 σ	2.89				2.89			
Level 2 σ	0.10				0.10			
χ2	197.84	***			196.26	***		
Deviance	20248.57				20249.00			
Parameters	2.00				2.00			

Notes: N = 5,171. † p < .06, * *p* <.05, ** *p* <.01, *** *p* <.001.

	Model 8			
	β		SE	*t*
Intercept	-0.51		0.09	
Individual				
Age	0.01	*	2.25E-03	2.38
Female	-0.19	*	0.07	-2.52
White	1.49	***	0.07	21.96
Narcotics	0.26	*	0.10	2.57
Powder cocaine	0.29	**	0.11	2.73
Crack cocaine	-0.06		0.06	-0.92
Heroin	0.57	***	0.08	7.05
Market				
Hispanic (%)	-0.03		0.33	-0.10
Level 1 σ	2.94			
Level 2 σ	0.09			
χ2	188.71	***		
ICC	0.03			
Deviance	20333.77			
Parameters	2.00			

Notes: N = 5,171. * p <.05, ** p <.01, *** p <.001.

C. Chapter 4 additional seller models

	Model 4				Model 5			
	β		SE	*t*	β		SE	*t*
Intercept	1.09		0.86		-0.59		0.08	
Individual								
Age	3.37E-03	**	1.28E-03	2.62	4.48E-03	***	0.00	3.47
Female	-0.34	***	0.04	-8.68	-0.35	***	0.04	-8.88
Hispanic	-0.58	***	0.04	-14.58				
White	1.18	***	0.05	25.72	1.48	***	0.04	36.33
Narcotics	0.53	***	0.07	7.72	0.53	***	0.07	7.64
Powder cocaine	0.15	*	0.07	2.16	0.11		0.07	1.65
Crack cocaine	-0.07		0.04	-1.51	-0.07		0.04	-1.51
Heroin	0.28	***	0.05	5.45	0.23	***	0.05	4.56
Market								
Marijuana (%)	-0.13		0.32	-0.41				
Female (%)	-3.36		2.11	-1.59				
Age (Mean)	-0.03		0.02	-1.17				
Hispanic (%)					0.14		0.27	0.52
Level 1 σ	2.84							
Level 2 σ	0.10							
χ2	368.36	***						
ICC	0.03							
Deviance	52424.59							
Parameters	2.00							

Notes: N = 13,473. * p <.05, ** p <.01, *** p <.001.

	Model 6				Model 7			
	β		SE	*t*	β		SE	*t*
Intercept	0.33		0.36		-0.25		0.87	
Individual								
Age	3.40E-03	**	1.28E-03	2.65	3.33E-03	**	1.28E-03	2.59
Female	-0.34	***	0.04	-8.67	-0.34	***	0.04	-8.68
Hispanic	-0.59	***	0.04	-14.68	-0.59	***	0.04	-14.67
White	1.17	***	0.05	25.57	1.18	***	0.05	25.68
Narcotics	0.53	***	0.07	7.70	0.52	***	0.07	7.62
Powder cocaine	0.14	*	0.07	2.09	0.14	*	0.07	2.03
Crack cocaine	-0.07		0.04	-1.56	-0.06		0.04	-1.36
Heroin	0.28	***	0.05	5.40	0.28	***	0.05	5.42
Market								
Female (%)	-2.77		1.99	-1.39	-0.42		2.26	-0.19
Age (Mean)					0.00		0.03	-0.10
Narcotics (%)					0.87		0.70	1.25
Powder cocaine (%)					1.30		0.86	1.52
Crack cocaine (%)					-0.27		0.40	-0.67
Heroin (%)					0.03		0.30	0.10
African American (%)	-0.39	*	0.18	-2.13				
Level 1 σ	2.84				2.84			
Level 2 σ	0.09				0.09			
χ2	295.35	***			233.16	***		
ICC	0.03				0.03			
Deviance	52418.65				52417.14			
Parameters	2.00				2.00			

Notes: N = 13,473. * p <.05, ** p <.01, *** p <.001.

	Model 8			
	β		SE	*t*
Intercept	-0.72		1.09	
Individual				
Age	3.35E-03	**	1.28E-03	2.61
Female	-0.34	***	0.04	-8.68
Hispanic	-0.59	***	0.04	-14.71
White	1.17	***	0.05	25.60
Narcotics	0.53	***	0.07	7.68
Powder cocaine	0.14	*	0.07	2.08
Crack cocaine	-0.07		0.04	-1.52
Heroin	0.28	***	0.05	5.43
Market				
Female (%)	-1.68		2.13	-0.79
Age (Mean)	0.01		0.03	0.47
Hispanic (%)	0.86	*	0.38	2.28
White (%)	-0.09		0.49	-0.19
Level 1 σ	2.84			
Level 2 σ	0.09			
χ2	277.56	***		
Deviance	52420.76			
Parameters	2.00			

Notes: N = 13,473. * p <.05, ** p <.01, *** p <.001.

D. Postcensal data estimation

Taken verbatim from GeoLytics (2009).

Population, Housing, and Income Estimates

First a quick overview:
In building population estimates there are several pieces needed to begin. The changes that occur in an area will be the addition of births, subtraction of deaths and the addition/subtraction of those who moved. The starting point is the 2000 Short Form (SF1) BLOCK level data set. This has the most detailed and comprehensive numbers about where the entire population of the US lives, their age and their race. To progress from the 2000 data to current year estimates, we use the US Census Bureau's (USCB) County and State level annual estimates to roll the numbers forward to the current year. But the USCB data is only available at the County and State level, so the next challenge is distributing the data down to the smaller geographies.
The next step is to work with actuarial tables for births and deaths by age and race, and use them to create a model of "likelihood" of dying or likelihood of having a child. This then is what creates the engine driving the increase and decrease in population growth.

The third step is to look at immigration and emigration. Where are people moving "to" and where are they moving "from". The US Postal Service keeps track of all moves as a "to" and "from" location.

Now the more detailed explanation:

1. Working with the Census Bureau "estimation base" county level numbers.

This data is processed to obtain "race distribution" coefficients. However, the Census Bureau estimation base data do not include "other" race category. Also, "two or more races" category is much smaller than it is in SF1/SF3 Census data. By comparing the estimation base to SF1 county level data, it is possible to obtain some numeric ratios as to how "other race" and "two or more races" populations were distributed among the remaining races in the USCB's estimation base. These coefficients allow us to re-map the SF1 block level data and redistribute the "other race" and part of the "two or more races" population among the 6 remaining mutually exclusive races.

2. The SF1 block level data are processed with these new racial distribution coefficients. The resulting dataset is our estimation base. It includes 8 race/origin groups:

WA	White alone
BA	Black alone
NA	Native American alone
AA	Asian alone

PA	Pacific alone
R2	Two or more races
HS	Hispanic
WN	White, not Hispanic

A few words on Census analogs: The Total Population count corresponds to the Census table P001, count P0010001. The rest correspond to Census age-race-sex tables from P012A to P012I, with the P012F (Other Race table) dropped. We do not have the "Other Race" category in the estimates even though Census 2000 does, because the USCB dropped the "Other Race" data from its estimates. They switched to 8 races in 2001 and we had to follow. It is worth mentioning that the USCB redistributed the racial counts of Other Race completely and the counts for "2 or more Races" were partially redistributed between the rest of the races in their estimates. We did the same and therefore the racial breakdown differs from the Census 2000 but fits the 2001 USCB estimates. We believe that the USCB made these changes because there are no actuarial tables for "other" or "2 or more" races so they needed to redistribute those people into one of the race categories by which they could create estimates

3. Having dealt with Race we then turn to Age. The USCB groups the population into 18 age groups. These range from age 0 (under 1) to age 108. The age groups are each 5 year intervals (0-4, 5-9, etc) except the ages 85 and up (85-108) are treated as a single group.

4. Now that we have the entire population broken down into age and race categories we begin building the death-birth model. With the use of Actuarial tables we calculate the statistical likelihood for any given age/race group to die or to give birth. We then apply these coefficients to the 2000 data to create an estimation base for 2001, the coefficients are reapplied to create 2002, and so on until we get to the current year.

The model includes:

- transformation of age group distribution to "exact age" distribution. The resulting data set has population groups for each single year of age from 0 to 108.
- application of death probabilities for a specific age, sex and race group.
- application of birth rates for a specific age, sex and race group. The white population is treated as a mix of white not Hispanic and Hispanic population. The mix ratio is determined from the block data.
- 1 year shift.
- collecting the annual data into 5-year buckets.
- comparison of the results with Census Bureau estimates for this year.
- the results of comparison are used to tweak birth rates and death probabilities to make the numbers of both newborn and deceased in the model to be exactly equal to Census Bureau numbers for each county. The racial distribution is also tweaked to reflect that of Census Bureau data. It puts the annual estimates in sync with USCB data as much as possible.

5. The same model is applied to the results for 2008-2013. This time, however, the "tweaking coefficients" are predicted (as we do not have any materials for comparison) from the tweaking coefficients for 2002 to 2007. The prediction algorithm is based on a linear regression approach (they actually fit the linear plot very nicely),

Methodology - Household Estimates

The household estimates were calculated from:

- the Census data on the household
- the estimated data on the households
- the Census data on the age-race-sex
- the estimated data on the age-race-sex.

GeoLytics calculated the ratios of Census household variables to Census age-race-sex data and Census housing data and then used these ratios for estimated data of the same nature to get the estimated values. The underlying assumption being that the average family size by race will not have changed dramatically in the years since the 2000 Census was compiled.

Methodology - Housing Estimates

The only way that the number of housing units (HU) changes is if new buildings are built or old ones torn down. Some houses can be built on empty lots, but if a lot of houses are built usually a whole new development gets put in. So the first thing that we did was to look at the TIGER/Line files. This is the USCB file that shows each and every street in the US and has the numbers of each housing unit. By looking at this dataset we can determine if new streets have been put in and by looking at the numbering we can determine about how many units are being built. We can also see if new numbers have been added to an existing street.

1. The TIGER/Lines records for the years 2000 and 2007 were analyzed. For each block, the sum of associated address ranges was calculated. As a result, each block was assigned a Change Coefficient (CC), a number representing the changes in the aggregate number of addresses within this block. The number is a fraction between -1 and +1. The number 0 represents a block that has not been changed within this time interval. The number +1 represents a block that did not have any addresses in 2000 and has some in 2007, and the number -1 is a block with no addresses in 2007 and has some addresses in 2000. The block changes were later summarized to BG level.

2. The Census Bureau Housing Units Estimates (at the county) for the years 2000 to 2007 were used to assess the number of HU per county for the year 2008 via a linear regression algorithm.

3. For each county, the Census Bureau HU growth/decline was distributed among BGs of this county so that:

- BGs with CC = 0 did not change any HU counts
- BGs with CC not equal to 0 received some parts of the county growth on proportional basis so that BGs with CC > 0 received some HUs and BGs with CC < 0 lose some HUs. The results vary from small changes (mostly, a few percent is a typical change) to some pretty dramatic changes of 3-5 times (rarely). These obviously are where large housing complexes went in and dramatically changed the number of housing units in the block group.

Once we had the change in the number of Housing Units we can then look at the other housing variables such as of number of rooms, vacancy status, tenure (own vs. rent) status, etc. People all live in either a household or a group quarter (military barracks, college dorms, nursing homes, prisons, mental institutions, half-way homes, etc). The group quarters were left stable so the changes in population were then accounted for in the changes in Housing Units that had now been calculated. So for example, if the housing units stayed the same but the population numbers dropped than the vacancy status would go up.

The sum of all changes for all BGs in a county is equal to the Census Bureau HU county growth estimates.

Methodology - Income Estimates

When calculating Income Estimates there are several components. First we needed to calculate the changes in income from 1990 to 2000 so that we would have a basis for estimating forward. This again required some racial break-out changes because in 1990 the Race grouping was "Asian and Pacific Islanders" whereas in 2000 they are two separate races. Additionally the age changes had to be accounted for (everyone has aged since April 2000 so all of the age categories needed to shift up).

1. The first step was to create an Income Growth by Race number for each Block Group. Luckily, we were able to use both the GeoLytics Census CD 2000 Long Form (SF3) and the CensusCD 1990 in 2000 boundaries Long Form data product for the 1990 data. By using this normalized data set it means that we already have dealt with the geographic boundary changes from 1990 to 2000 and can then look at just the differences in incomes.

2. The BG-level racial growth data were applied to 2000 Census data to obtain 2008 racial income growth coefficients for each BG area. First, the growth data for 1990-2000 were processed using a compound interest model. Second, the calculated "interest rates" were applied to 2000 racial income data to get the 2008 growth data.

The Income Growth data by Race were not available for many BG for some races because if there are very few households of a given race in a block group than numbers were suppressed by the USCB in 1990. For these cases, we used the USCB Median Income Estimates for years 2000-2006 to get 2008 state median income growth data using a linear regression algorithm, and then used these state growth data for Block Groups and races.

3. The racial aggregate income data were processed in the same manner as racial median income data.

4. The Householder age distributions were estimated by using estimated Householder totals from our dataset and an age shift model. Namely, for each age group, a calculated number of householders was moved to the next age group. The first and last age groups were processed in a special way to take into account both new and dead householders. The sum of all householder age brackets is equal to our estimated HH total for 2008.

5. The area income range data were estimated using a distribution shift model. First, we assumed that the Census 2000 income brackets represent the "best fit curve" frequency distribution, and then applied a linear stretch transformation to the income scale. Finally, I calculated the new income bracket values produced by this linear stretching of the frequency distribution. The stretch coefficient was equal to the median income growth ratio for this area. What it all means is that the income increase moves some households from its income bracket in 2000 to the next income bracket in 2008. The number of such households can be estimated mathematically if we know the exact number of households for each income value. This exact number can be estimated using the "best fit curve" model.

6. Finally, the BG data (both medians and aggregates) were tuned so that summary state median values were exactly equal to the state median data for 2008, as estimated from Census Bureau publications for 2000-2006 (see item 2). It was done by using a two-section linear mapping scheme. The scheme

a. moves the actual state median so it becomes equal to the target value;
b. leaves state minimum and maximum median values for state BGs intact;

is a*x + b - linear a) between state minimum median value for all state BGs and state median, and b) between state median and state maximum median value for all state BGs (with different a and b within these two segments).

E. Missing data

	N	Mean	SD	Missing Count	Missing Percent	No. of Extremes* Low	No. of Extremes* High
Family structure							
2006	1,707	0.002	0.80	14	0.80	48	41
2007	1,706	0.001	0.80	15	0.90	50	40
2008	1,705	0.001	0.80	16	0.90	48	41
2009	1,705	0.001	0.80	16	0.90	48	43
2010	1,705	0.001	0.79	16	0.90	46	43
Stability							
2006	1,714	0.004	0.89	7	0.40	69	13
2007	1,714	0.004	0.89	7	0.40	69	13
2008	1,714	0.004	0.89	7	0.40	69	13
2009	1,714	0.004	0.89	7	0.40	69	13
2010	1,714	0.004	0.89	7	0.40	69	13
Socioeconomic status							
2006	1,616	0.028	0.82	105	6.10	6	54
2007	1,618	0.030	0.82	103	6.00	6	55
2008	1,614	0.026	0.81	107	6.20	7	53
2009	1,608	0.022	0.80	113	6.60	8	51
2010	1,607	0.021	0.80	114	6.60	9	52

* N of cases outside +/- 2 standard deviations from the mean.

F. Poisson HLM using percentile typologies to predict violence counts

	Model 1					Model 2				
	β		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	2.00		0.11	7.41		1.63		1.05	5.11	
Time-varying covariates										
2007	-0.12	**	0.04	0.89	-2.63	-0.11	**	0.04	0.89	-2.61
2008	-0.09	*	0.04	0.91	-2.09	-0.09	*	0.04	0.92	-2.05
2009	-0.18	***	0.05	0.83	-4.04	-0.18	***	0.04	0.84	-3.94
2010	-0.21	***	0.05	0.81	-4.50	-0.18	***	0.05	0.83	-3.90
Local	-0.10		0.06	0.91	-1.60	-0.07		0.06	0.93	-1.16
Import	0.10		0.06	1.10	1.50	0.11		0.07	1.11	1.63
Export	0.03		0.08	1.03	0.40	0.06		0.08	1.06	0.67
Public	0.09		0.05	1.10	1.73	0.07		0.05	1.08	1.48
Family structure						0.12		0.36	1.13	0.34
SES						-0.90	*	0.43	0.41	-2.09
Stability						-0.26		0.27	0.77	-0.96
African American (%)						0.53		0.36	1.69	1.47
Pop. 10-24 (%)						-2.59		4.18	0.08	-0.62
Level 1 σ	1.55					1.52				
Level 2 σ	0.40	***				0.39				
χ2	1826.81					1568.33				

Notes: N=169. * $p < .05$, ** $p < .01$, *** $p < .001$. ERR – Event rate ratio.

	Model 3					Model 4				
	β		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	1.08		0.40	2.93		1.40		0.31	4.06	
Time-varying covariates										
2007	-0.11	**	0.04	0.89	-2.60	-0.11	*	0.04	0.89	-2.58
2008	-0.09	*	0.04	0.92	-2.02	-0.08	*	0.04	0.92	-1.98
2009	-0.17	***	0.04	0.84	-3.96	-0.17	***	0.04	0.84	-3.92
2010	-0.18	***	0.05	0.84	-3.93	-0.20	***	0.05	0.82	-4.34
Local	-0.08		0.06	0.93	-1.19	-0.09		0.07	0.92	-1.36
Import	0.10		0.07	1.11	1.58	0.10		0.06	1.10	1.54
Export	0.05		0.08	1.05	0.61	0.04		0.08	1.04	0.45
Public	0.08		0.05	1.08	1.51	0.08		0.05	0.05	1.60
Family structure						-0.23		0.28	0.79	-0.82
SES	-0.75	*	0.37	0.47	-2.02	-0.69		0.38	0.50	-1.82
Stability	-0.22		0.26	0.80	-0.83	-0.12		0.25	0.89	-0.47
African American (%)	0.50		0.31	1.64	1.62					
Level 1 σ	1.50					1.54				
Level 2 σ	0.38					0.39				
χ2	1624.21	***				1468.47				

Notes: N=169. * $p < .05$, ** $p < .01$, *** $p < .001$. ERR – Event rate ratio.

G. Poisson HLM using median typologies to predict violence counts

	Model 1					Model 2				
	β		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	1.94		0.11	6.94		1.64		1.05	5.14	
Time-varying covariates										
2007	-0.11	*	0.04	0.90	-2.39	-0.10	*	0.04	0.90	-2.42
2008	-0.09	*	0.04	0.91	-2.05	-0.09	*	0.04	0.92	-1.99
2009	-0.19	***	0.05	0.83	-4.10	-0.18	***	0.05	0.84	-3.96
2010	-0.20	***	0.05	0.82	-4.26	-0.17	***	0.05	0.84	-3.63
Import	0.07		0.06	1.07	1.29	0.07		0.06	1.07	1.22
Export	0.06		0.05	1.07	1.22	0.06		0.05	1.06	1.20
Public	0.13	*	0.06	1.14	2.19	0.11	ǂ	0.06	1.12	1.85
Family structure						0.11		0.35	1.12	0.31
SES						-0.93	*	0.42	0.40	-2.18
Stability						-0.25		0.27	0.78	-0.93
African American (%)						0.51		0.35	1.67	1.46
Pop. 10-24 (%)						-2.86		4.18	0.06	-0.68
Level 1 σ	1.57					1.54	***			
Level 2 σ	0.39					0.38				
χ2	1776.14	***				1524.60				

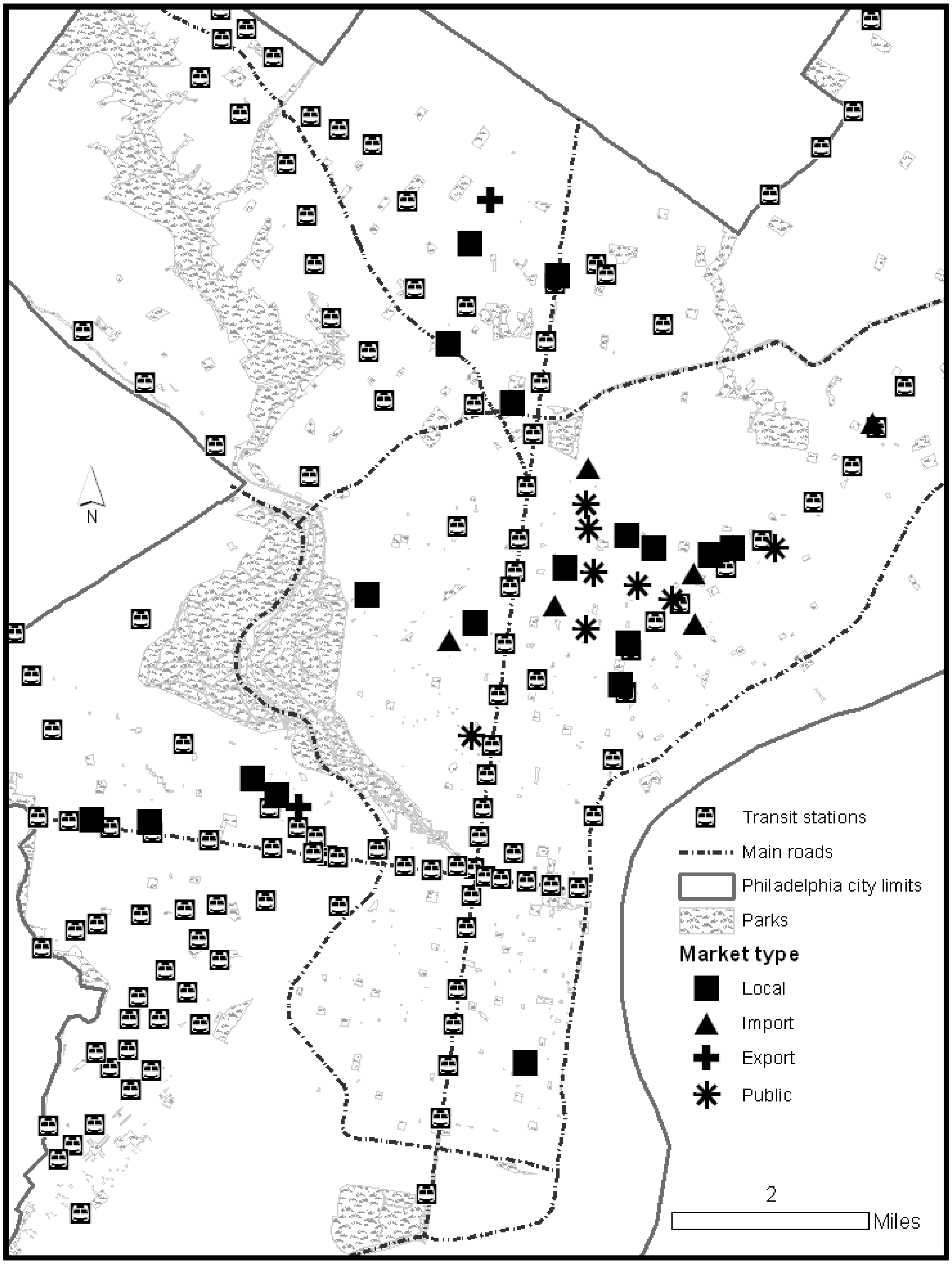
Notes: N=169. ǂ *p* < *.07,* * *p* < .05, ** *p* < .01, *** *p* < .001. ERR – Event rate ratio.

	Model 3					Model 4				
	β		SE	ERR	*t*	β		SE	ERR	*t*
Intercept	1.02		0.40	2.78		1.33		0.31	3.78	
Time-varying covariates										
2007	-0.10	*	0.04	0.90	-2.41	-0.10	*	0.04	0.90	-2.36
2008	-0.08	†	0.04	0.92	-1.95	-0.08	†	0.04	0.92	-1.93
2009	-0.18	***	0.04	0.84	-3.97	-0.18	***	0.04	0.84	-3.94
2010	-0.17	***	0.05	0.85	-3.66	-0.19	***	0.05	0.83	-4.08
Import	0.07		0.06	1.07	1.16	0.07		0.06	1.07	1.23
Export	0.06		0.05	1.06	1.18	0.06		0.05	1.06	1.14
Public	0.11	ǂ	0.06	1.11	1.82	0.11	†	0.06	1.12	1.93
Family structure						-0.24		0.28	0.78	-0.86
SES	-0.76	*	0.37	0.47	-2.07	-0.71	ǂ	0.38	0.49	-1.88
Stability	-0.21		0.26	0.81	-0.80	-0.11		0.25	0.90	-0.43
African American (%)	0.49		0.30	1.64	1.64					
Level 1 σ	1.52					1.56				
Level 2 σ	0.38					0.39				
$\chi 2$	1584.59	***				1428.90	***			

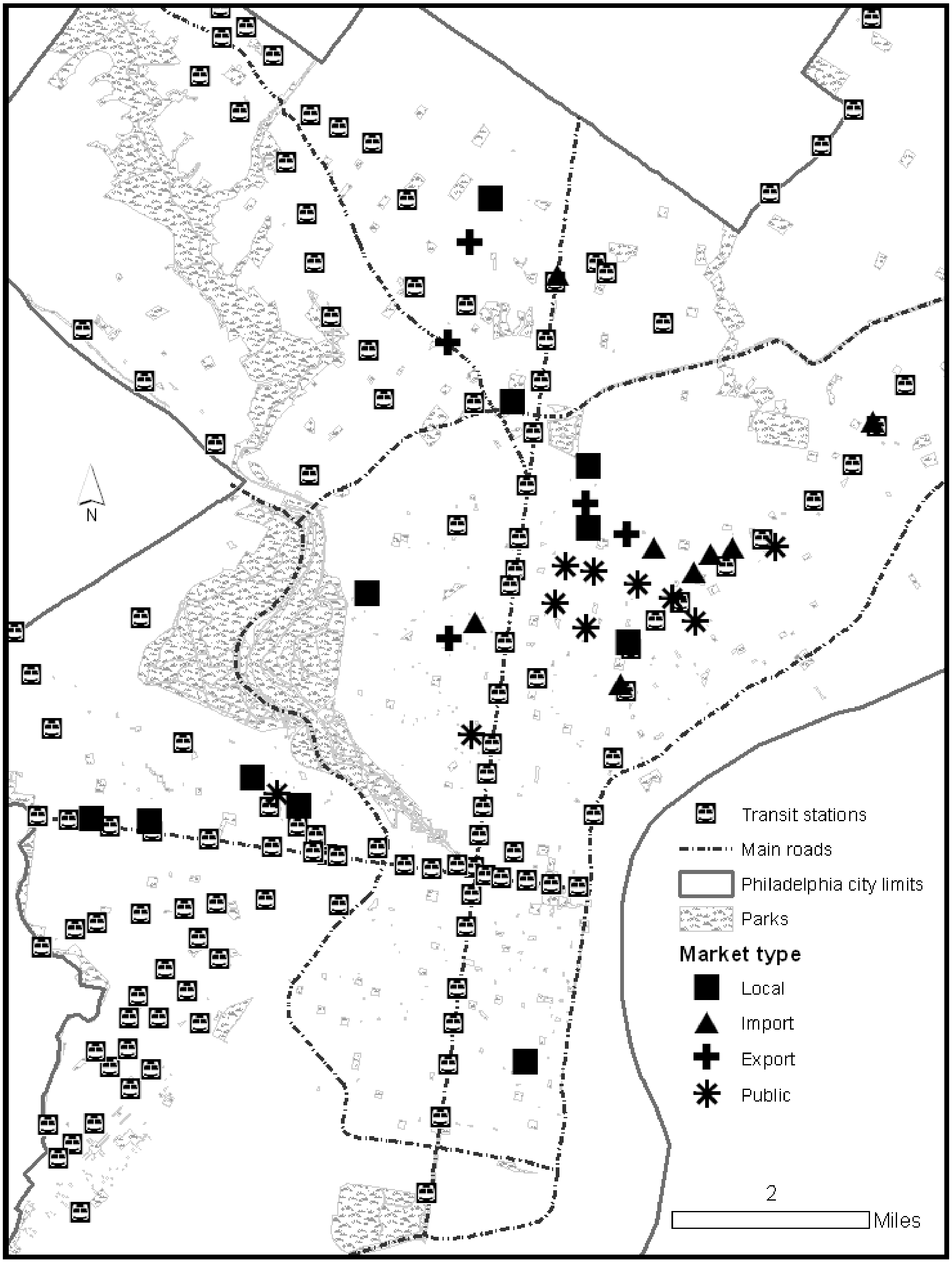
Notes: N=169. ǂ $p < .07$, † $p < .06$, * $p < .05$, ** $p < .01$, *** $p < .001$. ERR – Event rate ratio.

H. Drug market types in Philadelphia

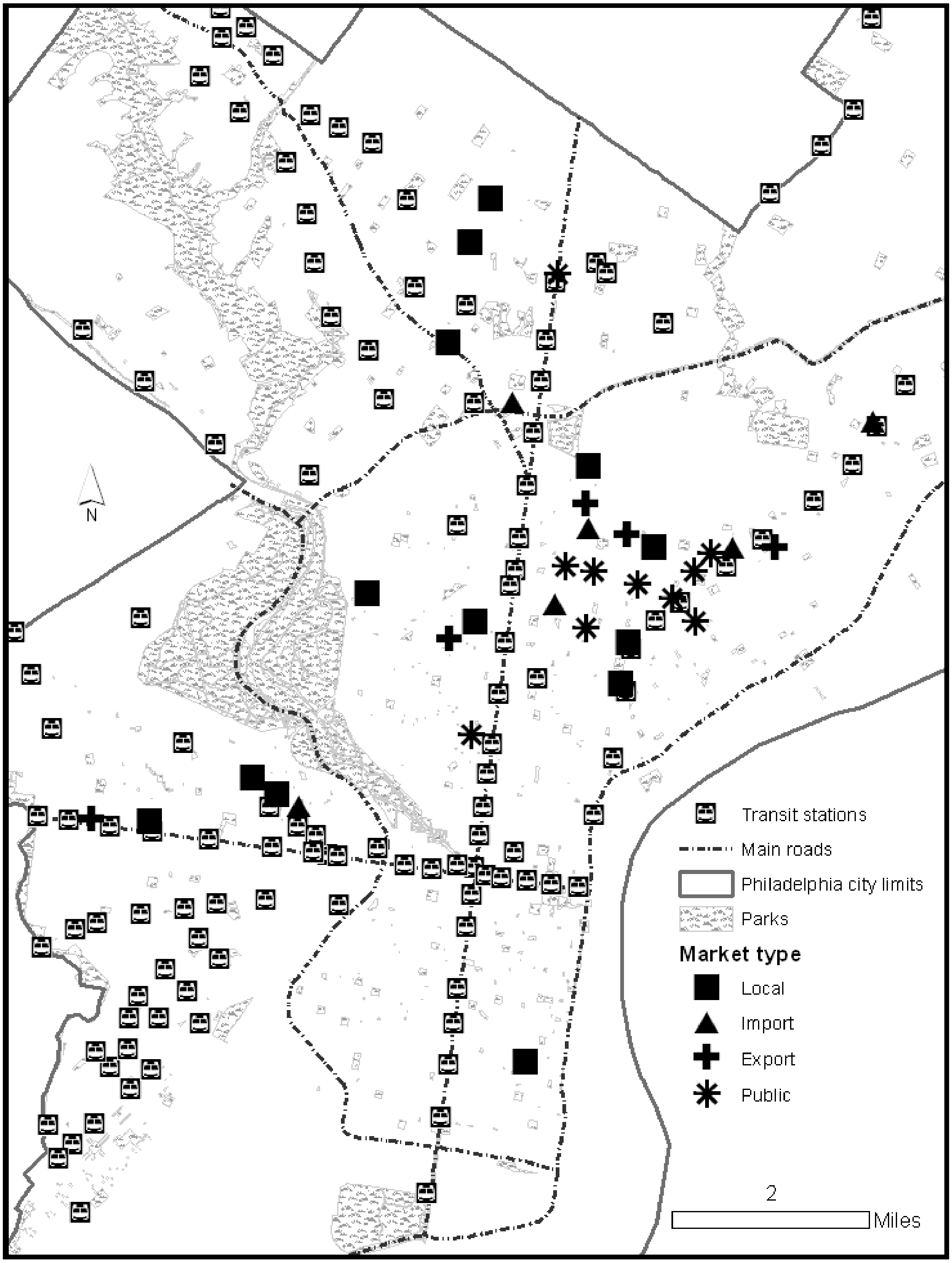
2006



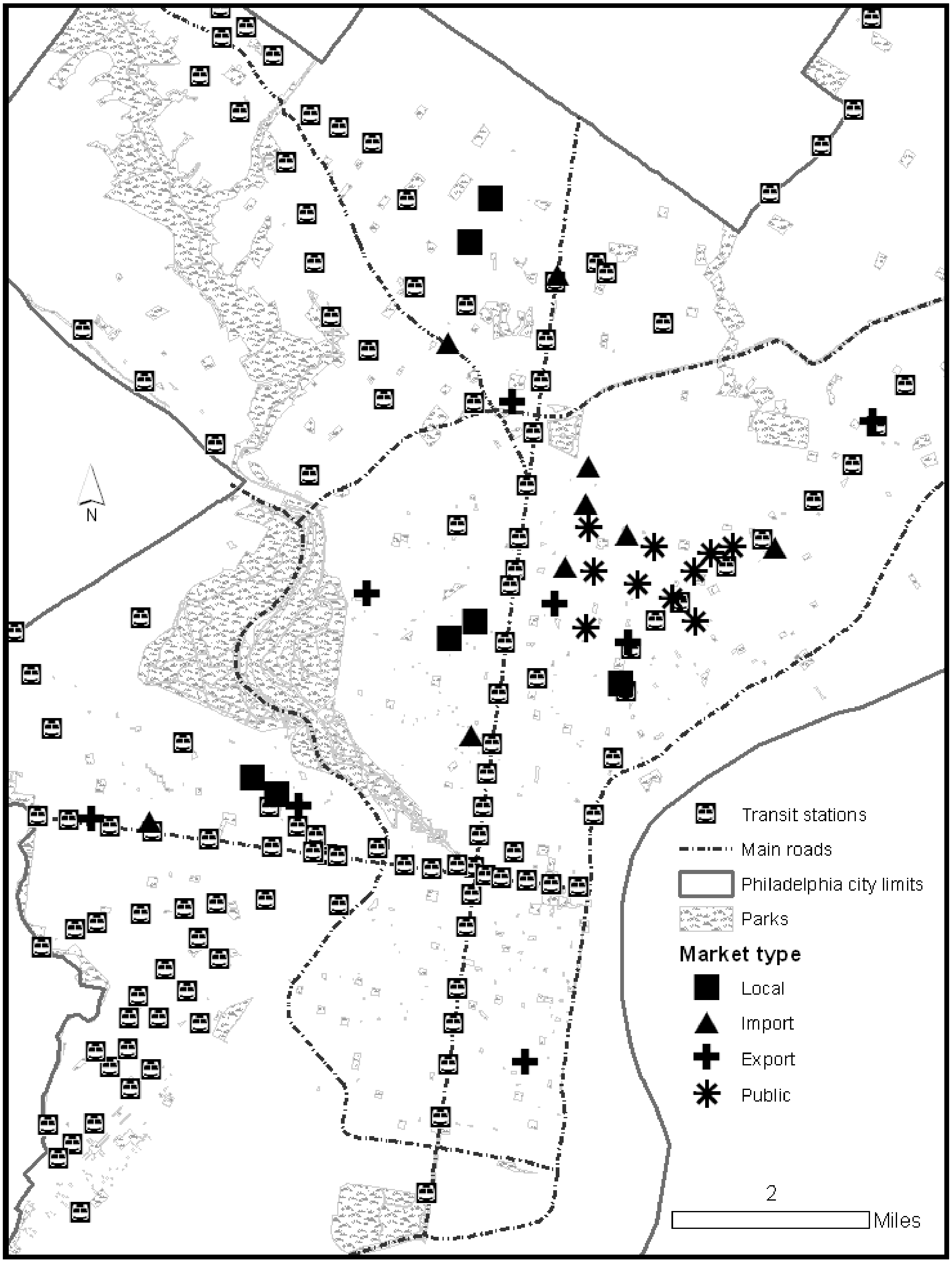
2007


N
Transit stations
Main roads
Philadelphia city limits
Parks
Market type
Local
Import
Export
Public
2
Miles

2008

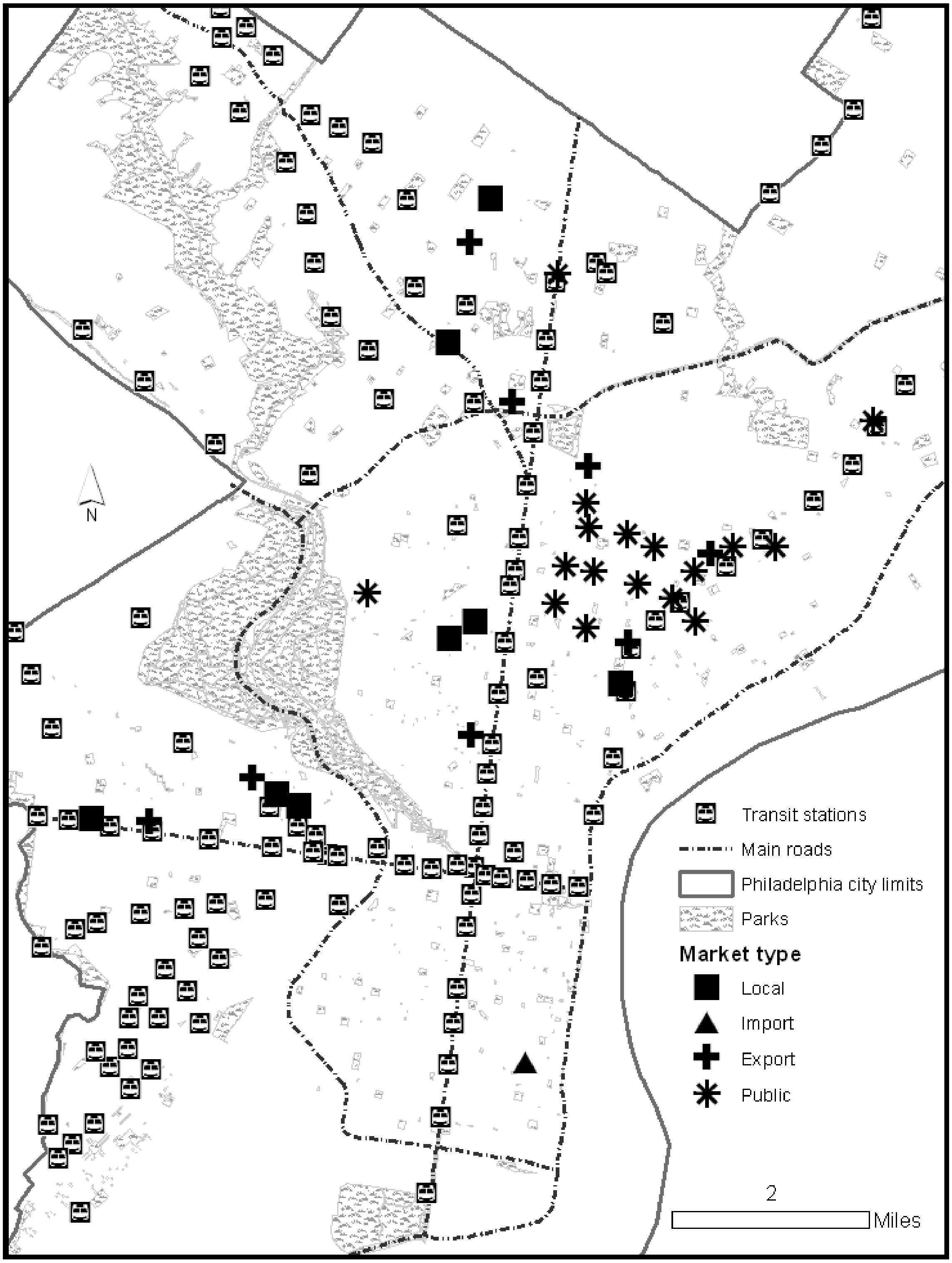

N
Transit stations
Main roads
Philadelphia city limits
Parks
Market type
Local
Import
Export
Public
2
Miles

2009



N
Transit stations
Main roads
Philadelphia city limits
Parks
Market type
Local
Import
Export
Public
2
Miles

2010


N
Transit stations
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Public
2
Miles