Journal of Research in Crime and Delinquency

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Journal of Research in Crime and Delinquency published online 22 February 2011

DOI: 10.1177/0022427810393016

Journal of Research in Crime and Delinquency
000(00) 1-37

DOI: 10.1177/0022427810393016
http://jrcd.sagepub.com

Gang Set Space, Drug Markets, and Crime around Drug Corners in Camden

Travis A. Taniguchi[1], Jerry H. Ratcliffe[2], and Ralph B. Taylor[2]

Abstract

Gang set space is defined as "the actual area within the neighborhood where gang members come together as a gang" (Tita, Cohen, and Engberg 2005:280). The current article examines one subarea of gang set space: where gangs maintain street corner-centered open-air drug markets. Two types of corners—corner markets dominated by one gang and corner markets with multiple gangs—were contrasted with one another and with non-gang, non-dealing corners. Functional and corporate perspectives on gangs would both predict single gang corner markets to have lower violent and property crime than non-gang corners, whereas a traditional view would predict more violence. Territorial and economic competition models expect the highest crime levels around corner markets occupied by multiple gangs. Using Thiessen polygons to define the sphere of influence of each corner, and controlling for community demographic fabric and nearby crime, results showed higher crime counts around space used for drug distribution and higher still when the set space was occupied by

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multiple drug gangs. Further, crime counts were higher in less stable locales. The portions of drug gang set space centered on small, known, open-air corner drug markets, especially when control is questioned, link to more crime.

Keywords
gang set space, drug corners, spatial analysis

Introduction

This article addresses the relationship between gang space utilized for drug dealing and crime. Gang set space has been defined as "the actual area within the neighborhood where gang members come together as a gang" (Tita, Cohen, and Engberg 2005:280), but here we focus specifically upon that portion of gang set space used for the open-air distribution of drugs. In the city examined here, Camden, NJ, these small open-air markets are highly localized, territorial, and center on street corners.

Thrasher (1927) noted that gangs (in general) tended to be highly territorial, that is, their functioning as a group centered on a small number of locations within the broader community. Generally, at least in low-income urban neighborhoods, these locations tended to center on street corners (Liebow 1967; Werthman and Piliavin 1967; Whyte 1955). Street corners, from a practical perspective, are optimal places for gangs to gather for simple physical reasons, including visibility of all approaching pedestrian and vehicular traffic, and perhaps weaker resident-based surveillance of gang members (Taylor and Brower 1985). Control of desirable street corners can often lead to financial advancement and greater prestige and status within the community (Ley and Cybriwsky 1974). Of course, with the advent of open-air drug markets from the 1980s onward, one of those key financial opportunities has been drug distribution (Rengert 1996). Focusing specifically on corners as drug selling locations, a large volume of sales may quickly transform a street corner into an open-air drug market (Eck 1995; Harocopos and Hough 2005; Rengert et al. 2005). At that point, a gang heavily invested in the drug trade may defend a corner not just to prove that it is theirs but also because the corner has optimal market features like proximity to many potential customers or a high volume of through traffic (Eck 1994).

Gang Set Space

The distinction between gang territory in general, and gang set space specifically, is important. Gang set space comprises areas that are physically small subsets of a larger gang territory. These areas are critical to the gang, yet as Tita et al. (2005) point out, determining the impact of gang set space on aggregate crime patterns has proven difficult. One of the biggest challenges has been to specify the appropriate ecological unit for evaluation. Tita et al. (2005) used census block groups, yet their own findings suggest that gang set space should be conceptualized on an even smaller geographic level: "A unit of analysis that allows for much finer resolution in locating gangs is likely to be more appropriate in ecological studies of gang activities, whether the focus is on gang homicide or simply hanging out" (Tita et al. 2005:276). Tita et al. also argued that the distribution of drugs could be a motivating factor in the selection of set space (also see Venkatesh 2008).

In response to these suggestions, we propose an extension and refinement of the conception of set space and the study of the relationship between drug gangs and crime. Taking a cue from Brantingham, Dyreson, and Brantingham's (1976) "cone of resolution," it is argued that existing research has focused predominantly on investigating the impact of gang territory on a macro-geography such as a neighborhood. Tita et al. (2005) brought the focus down another level by considering the impact of gang set space (a subset of a larger gang territory) on a smaller geographic scale (census block groups). The current analysis examines this relationship at an even finer resolution. Here we investigate the impact of that portion of gang set space used for the open-air distribution of drugs upon crime at the micro-geographic scale: the spaces at, and immediately adjoining, corners.

This analysis draws on research conducted by Weisburd et al. (1994) to define the intersection of streets as the unit of analysis. This definition has a number of practical benefits. Weisburd et al. (1994:64) argue that the street intersection "is not sensitive to small coding errors or short movements of offenders. The intersection area unit of analysis also avoids predicting the direction of drug sales activity on a particular block . . . " Furthermore, the use of highly localized micro-spaces as the unit of analysis provides enhanced sensitivity in testing the relationship between the urban backcloth and the spatial distribution of crime (Brantingham et al. 2009). By disaggregating space within census block groups, a clearer understanding of how gang drug dealing set space affects crime may be possible. We emphasize that this disaggregation is undertaken not just for methodological reasons.

Rather, corners have been the key to urban drug gangs for many years, and their current importance derives from their optimality as dealing locations. The units used provide a better spatial alignment between the analysis and the relevant domains in the setting.

The impact of gang set space is not evaluated here. Gangs use spaces within their territory for a wide range of gang activities. Rather, this study tests the criminogenic impact of only that portion of drug gang set space used as a venue for the open-air distribution of drugs, recognizing that for modern urban gangs involved in drug trafficking, the open-air drug distribution and the associated revenues represent key gang activities (Venkatesh 2008). This centrality, and the associated policy implications of better understanding the open-air distribution of drugs, makes the study of these more specific micro-geographies highly relevant.

The criminogenic effect of drug gangs can be looked at from various levels. The individual relationship between a general gang affiliation and crime has been well established: gang members engage in more crime than their non-gang counterparts (Fagan 1989; Horowitz 1987; Howell 1994; Klein, Maxson, and Cunningham 1991; Maxson 1999; Thornberry and Burch 1997). At the ecological level, however, theoretical and empirical analysis of the relationship between *drug gang* space and crime remains sparse. The following section highlights the fact that competing theories propose opposite, yet equally plausible, predictions for the effects of gang set space upon localized crime levels.

The first perspective argues that crime will be substantially higher around drug dealing corners versus non-gang corners. The illegal nature of drug dealing places the transaction outside of the reach of the legitimate economy (Blumstein 1995; Blumstein and Cork 1996; MacCoun, Kilmer, and Reuter 2003) and therefore limits the legal recourse that can be taken if a transaction is seen as unsatisfactory by either party. Unable to seek recourse through lawful means, participants engage in violent behavior in order to resolve disputes (Goldstein 1985; Harocopos and Hough 2005; Levitt and Venkatesh 2000). Violence is also seen as a tool to both establish and protect drug dealing locations (Chaiken and Chaiken 1990). Because of this close association with violence, drug markets are seen as responsible for more than crime levels; they are responsible for the general deterioration of inner cities (Tonry 1990).

Routine activity theory offers another possible process through which gang-drug corners influence crime (Cohen and Felson 1979). The open-air distribution of drugs has to take place in the absence of capable guardianship or effective place management (Eck 1994; Felson 1995). Drug markets can be a cause, and a result, of poor place management. Rengert (1996) demonstrated the ability of drug markets to hollow out surrounding housing stock. This effectively eviscerates the community's ability to regulate public spaces (Taylor 1988). The lack of legal recourse provides the potential for numerous actors to play the roles of target or offender on a regular basis. For example, the dealers are known to have drugs and money and ethnographic evidence suggests that offenses against dealers are not uncommon (Simon and Burns 1998).

It is possible that gang territory may link differently with property crime. Gang space utilized for the distribution of drugs may act as both property crime generators and property crime attractors (Brantingham and Brantingham 1995). For individuals, drug use has been associated with higher levels of property crimes such as burglary and theft (Anglin and Speckart 1988; Blumstein 1995; Goldstein 1985). Drug markets may, therefore, draw in people predisposed to committing property crimes. Furthermore, drug markets may facilitate the exchange of stolen goods for money (Sullivan 1989). We explore these conceptually distinct outcomes by conducting separate parallel analyses on both violent and property crimes.

An opposing perspective argues that gang set space may reduce or at the least have no impact upon the level of crime in the surrounding area (see Tita and Ridgeway 2007 for a comprehensive review of this argument). This argument often sounds counterintuitive at first. It is important to note, however, that although gangs may be criminally involved, it is not inevitable that gangs will bring crime to any particular place nor that they are involved in street drug dealing. Indeed, gangs may make a special effort to prevent bringing crime to locations near their set space (Bursik and Grasmick 1993; Taylor 2001). Gangs have been known to suppress crime, maintain social order, and provide financial stability to economically disadvantaged areas (Pattillo-McCoy 1999; Suttles 1968; Taylor 2001; Venkatesh 1997, 2006, 2008).

It has been well established that gangs attempt to exert control over physical space (Ley and Cybriwsky 1974; Thrasher 1927), and this imperative is likely stronger for drug groups that control areas for narcotics transactions. Well-established territories serve to manage conflict by keeping individuals from different groups better isolated. This leads to the prediction that areas solidly controlled by a single gang will have less crime than areas utilized by multiple gangs.

Second, drug dealing gangs may have an economic motivation to reduce the level of crime around their set space. Violence can draw unwanted attention from both community members and law enforcement officials (Cohen and Tita 1999; Goldstein 1985; Levitt and Venkatesh 2000). Crime can also cause fear among potential customers pushing them into safer areas to conduct drug transactions. Venkatesh (2006:176) writes,

> ...because they depend on an active, bustling public theater for customers, street hustlers must be careful when inhabiting common areas. Their dual roles can lead them to be not only predators on public space but also contributors to the regulation of social behavior that threatens public access and passage.

A limited body of quantitative evidence is available to support this theory. Levitt and Venkatesh (2000) found a 20 to 30 percent drop in the price and quantity of drug sold during periods of high violence. Drug dealing gangs have both legal and economic reasons for keeping violence around dealing locations as low as possible (Cohen and Tita 1999; Goldstein 1985; Levitt and Venkatesh 2000). Pattillo-McCoy (1999:86) states "there is significant irony in the fact that having an organized gang in the neighborhood has, in some respects, translated into fewer visible signs of disorder, less violence, and more social control." This does not mean that community members support drug dealing or the associated violence. Pattillo-McCoy (1999) argues that this should instead be viewed as a compromise between the residents' desire for safety and their moral indignation over the violation of law occurring within their community.

Corners, of course, do not stand alone, but rather are nested within the broader demographic fabric of the surrounding community. This study will rely upon the broader work in factorial ecology that has consistently, over several decades and several continents, found three broad community structural dimensions that link to crime: status, race/ethnicity, and stability/familism (Hunter 1971, 1972, 1974; Janson 1980; Taylor and Covington 1988). A recent meta-analysis of links between crime and community structure (Pratt and Cullen 2005) found that socioeconomic status and race linked the most consistently to differences in community crime rates. Indicators for both of these dimensions are included here. Stability, which under some conditions may be a necessary but not necessarily sufficient condition for the emergence of local supervisory capacity (Bursik and Grasmick 1993), will also be taken into account. High levels of single-parent female-headed households and high levels of youth within the community can link to crime (Sampson and Groves 1989), so indicators for this dimension are included as well.

The analysis will compare the crime levels around three types of corners: those where open-air drug distribution does not take place, those where distribution does take place and is controlled by one drug gang, and those where drug distribution by multiple drug groups takes place. In the study setting, all open-air drug distribution is gang controlled, an assertion that is discussed in more depth in the following section.

Setting, Data, and Methods

The City of Camden, New Jersey lies just across the Delaware River from Philadelphia, Pennsylvania. One of a number of municipalities within the County of Camden, the city has just over 10 square miles and 80,000 residents; for the remainder of this article, "Camden" refers to the city and not the county. Camden proves to be a unique place to study crime. Camden is consistently rated as one of the most dangerous cities in America, taking the number one spots for 2004 and 2005 and second place in the most recent rankings, rankings based on population-corrected reported crime rates (Morgan and Morgan 2008; Morgan Quitno Press 2005, 2006, 2007). In 1995, Camden was designated as part of the Philadelphia/Camden High Intensity Drug Trafficking Area (Office of National Drug Control Policy 2001; U.S. Drug Enforcement Administration 2007). It was recognized that the "region has a well-developed transportation infrastructure . . . that is ideally suited for the movement of illicit drugs and drug proceeds to and from the region" (NDIC 2007:3). Suffice it to say that drug use and distribution is a well-established force in the Camden economy.

Gang-Drug Corners

The Camden County Prosecutor's Office (CCPO) established the definition of gangs, which this article adopts. Although other more complicated definitions exist (e.g., Ball and Curry 1995), there was a need for an operationally efficient definition. A gang, for operational purposes in Camden, is defined as:

> A group of five or more people with (1) some type of structure, (2) a common identifier, (3) a goal or philosophy that binds them and (4) whose members are individually or collectively involved in criminal activity. (City of Camden, n.d.:1)

Data on drug gang corner locations were provided by the Office of Intelligence Services in the Camden County Prosecutor's Office. The CCPO collected these data from a number of different sources but predominantly relies on officer observations corroborated by recognition of gang tattoos, identified association with known gang members, and offender self-reports during interview. These records were used to identify locations where gang members were known to both sell and purchase drugs. The data were not drawn from a generalized force-wide information repository but rather were taken from a dedicated database maintained by the Office of Intelligence Services and populated by individualized entries verified by a member of the Intelligence Services team. All data originated from direct contact between a team member and a cadre of experienced detectives and local officers, the overall process designed to understand spatial and temporal patterns of gang-related drug activity in the city. Further details about how these drug distribution locations were classified can be found later in this section.

Data were collected directly from staff in the Office of Intelligence Services during 2006. The initial data set contained the known gang-related drug dealing locations for the entire city of Camden where a known gang member had been seen and/or arrested dealing drugs at the location. Excluded from this analysis were sites with gang members dealing drugs from residential locations ($n = 419$, approximately 70 percent of all known drug dealing locations in the City of Camden) because the focus of this study was on the distribution of drugs through open-air markets. Ninety seven percent of the data on the gang-drug dealing locations were successfully geocoded.

Excluding residential drug dealing locations may, at first, seem counter-intuitive. The position taken here is that open-air drug markets are different enough from residential drug distribution that they warrant evaluation on their own. Theoretical frameworks, and empirical research, suggest that open-air drug markets are quantifiably different than drug markets occurring in private settings (Eck 1995; Kleiman and Young 1995; Rengert 1996). Open-air drug markets tend to be highly visible and noxious to the surrounding community (Harocopos and Hough 2005). Open-air markets also tend to be the target of substantially different public policy considerations. Open-air markets can be more easily controlled by police operations and changes to the physical environment. For these reasons, the analysis only considers open-air drug distribution locations.

Keeping only the street drug dealing locations can still retain much of the volume of drug activity. Sales in private networks tend to be smaller and only occur when the drug dealer and the drug buyer are familiar with each other. In contrast, drug dealing in open locations at well-known drug markets frequently occurs between buyers and sellers that are unfamiliar (Rengert 1996). This increases the volume of drug sales from these locations. Therefore, even though 70 percent of locations were removed, this should not be interpreted as 70 percent of drug sales transactions were removed. We believe, based on our long-term collaborative efforts with intelligence officers, that the locations included in this analysis represent the main venue of drug transactions within this specific setting. Whether this applies to other cities in which the relationship between gangs and drug distribution is not as well entrenched is a potential avenue for future research.

It is furthermore possible that other non-gang sources of drug distribution exist, and our data set is likely to exclude individual entrepreneurs who offer drugs for sale on the street and who are not affiliated with a particular drug gang. Our extensive discussions with police and intelligence officers suggest that drug distribution is largely controlled by gangs in Camden and small, non-affiliated entities are not a significant factor. The claim that Camden drug markets are controlled by gang activity is grounded in evidence from various agencies. One author on the current study has had extensive interactions with many different organizations working in Camden, including; federal law enforcement (FBI, DEA, and HIDTA), state law enforcement (New Jersey State Police), county law enforcement (Camden County Prosecutor's Office), city law enforcement (Camden Police Department), community organizations, and the Camden Safer Cities initiative (a multijurisdictional criminal justice policy research group). These various institutions are consistent in reporting that, at least in Camden, named gangs control the majority of drug distribution. The majority of drug dealing, at least by volume, is a public venture conducted at relatively stable and permanently manned street corner locations. Whether this applies to all drug distribution networks in areas outside Camden remains an open question for future research and is discussed in more depth in the following section.

Gang-drug set space corners were classified into two groups: *dominated* (single gang) open-air corner markets and *diverse* (multi-gang) open-air corner markets. A corner was classified as dominated if one, and only one, gang was known to distribute drugs from that location based on records provided by the CCPO. Dominated corners accounted for 110 (6.3 percent) of the 1,751 total corners within the city. Diverse corners were classified as such if two or more gangs were known to deal drugs from that location. Camden has a large number of diverse corners (n = 70, 4.0 percent of all corners). Although Camden has a well-established and profitable illicit drug economy, CCPO intelligence officers were quick to point out that gang battles over turf were not uncommon; control over specific highly desired locations can be enough to secure a substantial income for the organization.

We should, however, also recognize that some corners may be shared through cooperation and agreement—our data did not provide sufficient detail to describe the relational nature between different drug dealing gangs at a location.

Corners with an absence of gang drug dealing set space provided the comparison group. A program written in ArcGIS (a geographic information system) generated the coordinates of every street intersection within the city. The known drug-gang corners were then removed from the file leaving 1,571 unique corners not associated as gang drug dealing set space.[1]

The gang status of each corner was coded using two dummy variables. The variable "dominated dummy" was coded: 0 = *non-gang or diverse corners* and 1 = *corner dominated by one gang*. The variable "diverse dummy" was coded: 0 = *non-gang or dominated corners* and 1 = *diverse corners*. Thus, each variable represented the unique effect of the type of corner for which it is named. This method of coding made non-gang corners the reference group for comparison against dominated and diverse gang corners.[2]

Recorded Crime

Crime data used in this analysis were obtained directly from the Camden Police Department's (CPD) records management system. This analysis excluded calls for service and instead focused only upon events classified using the Federal Bureau of Investigation's (FBI) Uniform Crime Report (UCR) standards. Crime data recorded between January 1, 2005, and December 31, 2006, were used, providing over 12,000 unique crime events. The first dependent variable consisted of UCR part one violent crimes: murder, rape, robbery, and assaults (hereafter referred to as violent crime). The second dependent variable was created from UCR part one property crimes; burglary, theft, auto theft, and arson (hereafter referred to as property crime). The selection of these crimes was based, at least partially, on the fact that they leave the responding officers minimal discretionary powers in recording and reporting the event (Klinger 1997). Therefore, it is possible to rely on these crime measures to be an accurate indicator of criminal activity and less of an indicator of discretionary police actions. A final hit rate[3] in excess of 95 percent was achieved after substantial manual efforts.

Analytic Overview

Two particular challenges were encountered while attempting to determine the criminogenic effects of gang-drug corners. First, the researcher must resolve the basic question of how far the criminogenic effect of a gang corner extends. The application of a spatial buffer around a point location—a common way to address issues of spatial interaction—implicitly assumes that there are characteristics of the intersection that influence crime occurrence beyond the street corner. But how far does this influence extend?

A second methodological concern: how best to allocate census data to the corner under study? At first glance, this may not seem like such a difficult decision. Indeed, many researchers in the area of spatial crime analysis ignore this issue by taking the approach with the simplest solution (giving the point the attributes of the census area in which it is located). This method of allocation, however, is undesirable for irregularly shaped areas such as census geographies, and is especially a problem when we are interested in not only the corner location but also the spatial context of the buffer surrounding each corner.

Although the point location from which the buffer is drawn will fall into a single census geography, it is unlikely that the entire buffer will also lie within this single buffer. Figure 1 helps to illustrate this problem. In Figure 1, corner A falls within the boundaries of census block 2, yet the buffer generated by corner A largely falls within census blocks 1 and 3.

This method runs into an attribute allocation problem not dissimilar to the modifiable areal unit problem (MAUP; Openshaw 1984b). This overlap of polygon boundaries can have a substantial impact upon statistical analysis because spatial autocorrelation coefficients and regression model parameters can be affected by the areal aggregation of spatial units (Anselin 1998). Areal units from one type of geography will often overlap and cross the boundaries of a different geographical data set (Saporito et al. 2007). The relevance for the current study is the problem that aggregating from the census layer to the theoretically relevant layer becomes a more challenging task.

To minimize the impact of both issues, Thiessen polygons were used to approximate the range of influence surrounding a corner. This information was then combined with data from the 2000 Census that had been modified to fit the Thiessen polygon. This methodology ameliorated the problem of combining data from administrative boundaries (census geographies) with spatial areas of theoretical influence.

Thiessen Polygons

Thiessen polygons form unique spatial regions devoid of arbitrary user inputs while maintaining statistical independence. A Thiessen polygon

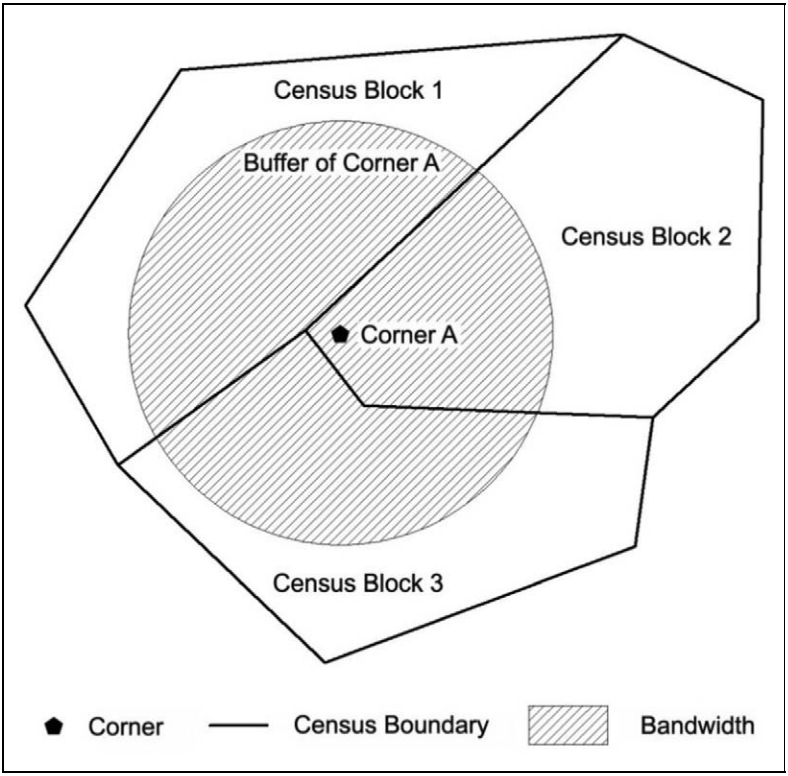

Figure 1. Hypothetical corner within irregularly shaped census data. Figure 1 demonstrates the difficulty of combining irregularly shaped census geographies with areas of theoretical interest. The buffer of corner A falls within 3 different census geographies. Applying the characteristics from any single census geography to the entire buffer assumes effects beyond the lines of the census boundaries. This analysis solves the allocation problem through the use of Thiessen polygons.

encompasses all space closer to its centroid than to any other centroid (Aurenhammer 1991; Scheike 1994) and are tessellated to avoid spatial gaps or overlapping regions (Okabe, Boots, and Sugihara 1992). Figure 2 shows four corners along with the Thiessen polygons generated for each corner. In this example, crime event 1 is associated with corner A, crime event 2 with corner B, and crime event 3 with corner D. Thiessen polygons systematically allocate crimes to street corners with each crime allocated to the street corner that is physically closest based on straight line Euclidian

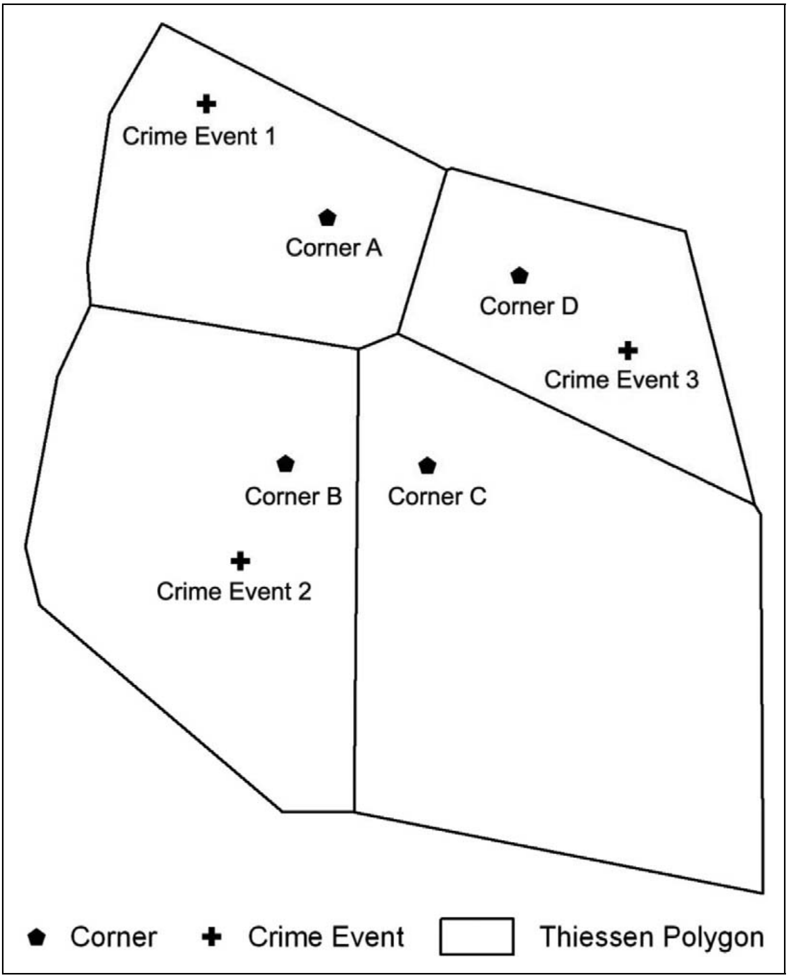

Figure 2. Example of Thiessen polygons and crime points. In Figure 2, a set of Thiessen polygons was generated for Corners 1 through 4. These polygons solve the difficult task of assigning crime to individual corners. Crime is assigned to the corner from which the Thiessen polygon is generated. Because of the way Thiessen polygons are generated crime events are assigned to the corner that it is physically closest to based on Euclidean straight line distance. This method also solves another problem as crime can only be associated with one corner thus preserving the ability to utilize statistical analysis.

distance and avoids requiring arbitrary decisions about the distance effects of the corner location.

While the use of Thiessen polygons provides substantial benefits to understanding the relationship between gang drug activity and crime it is not without limitations. A Thiessen polygon containing a gang's or multiple gangs' locations should not be thought of as synonymous with gang set space. Thiessen polygons may be both overinclusive (encompassing areas not used for drug distribution) and underinclusive (missing areas used for drug distribution—a possibility discussed later). Nevertheless, we believe that the use of Thiessen polygons as a proxy for gang set space is appropriate. We recognize that gang set space is a class of behavioral setting (Barker 1968) that Thiessen polygons can only capture imperfectly; however, there is still substantial value in conducting the micro-place examination undertaken here. The use of Thiessen polygons has a conceptual relationship with, and a common spatial foundation to, the innovative work of Tita et al. (2005). Furthermore, the methodology used here allows for the analysis of criminal intelligence data (often stored with little concern for spatiality), police crime records, and sociodemographic data.

Census Data

Data on the social structural aspects of Camden were taken from the 2000 U.S. Census. These indicators covered the main three dimensions of factorial ecology (discussed in the previous section)—status, race/ethnicity, and family structure/stability. Status was captured with four 2000 census variables: median household income, median home value, percent unemployed, and percent with better than high school education. Median household income and median home value were collapsed into a scale item labeled as "status" (Cronbach's $\alpha = .67$). The variable "Percent unemployed" represented the percentage of people over the age of 18 currently unemployed. "Percent better than HS ed." represented the percentage of people 25 and older with an education above the high school level.

Several variables were used to capture the influence of race and ethnicity. The "foreign born" index (Cronbach's $\alpha = .84$) was comprised of two census variables: (1) the percentage of people born in a foreign country and (2) the percentage of people responding as being a race other than White, African American, or an ethnicity other than Hispanic. A "race index" (Cronbach's $\alpha = .93$) was comprised of the percentages of the population responding as African American or Hispanic.

For stability and family structure, one index and two individual census variables were used. The index was comprised of census variables representing the percentage of children age 0 to 5 and children age 6 to 12. These two variables were combined into an index hereafter referred to as "young children" (Cronbach's $\alpha = .56$). Two individual census variables were also included: the percent of female headed households ("% fem. headed HH") and the percent of residents with tenure less than 5 years ("% tenure < 5 years"). With all predictors entered there were no variance inflation factors (VIFs) above 2.5.

Census data were allocated to the Thiessen polygons generated from the corner locations following the vicinity approach of Ratcliffe and McCullagh (1999). Briefly, census data were disaggregated into units smaller than block groups. These smaller geographies were then re-aggregated back into the shape established by the Thiessen polygons. The disaggregated census data provided a method of areally weighting the values that would ultimately be assigned to the Thiessen polygons. Figure 3 demonstrates how census data were allocated to Thiessen polygons.

In Figure 3, the hypothetical census geography unit has 10 people distributed across four Thiessen polygons. About 40 percent of the area of the census geography lies within Thiessen polygon 1. Therefore, four people were allocated to Thiessen polygon 1. This process was repeated until all people in the census geography are allocated to a Thiessen polygon.[4]

Failure to account for spatial clustering can lead to "false indications of significance, biased parameter estimates, and misleading suggestions of fit" (Messner et al. 1999:427). This analysis corrected for spatial clustering through the use of a two-stage least squares spatial lag set forth by Land and Deane (1992). The first stage was to assign each polygon a weighted crime intensity value using a computer program that applied an inverse distance weight matrix to the crime counts in all surrounding polygons for each target polygon. The output represented for each polygon the "generalized population-potential" of crime in the surrounding polygons (Land and Deane 1992:231). In the second stage, the generalized population-potential was predicted[5] with variables from outside the main model. The predicted values from the regression analysis were then saved as an instrumented (error free) variable capturing generalized spatial lag.

Table 1 presents the mean, median, minimum, maximum, and standard deviation of the variables utilized in these analyses.

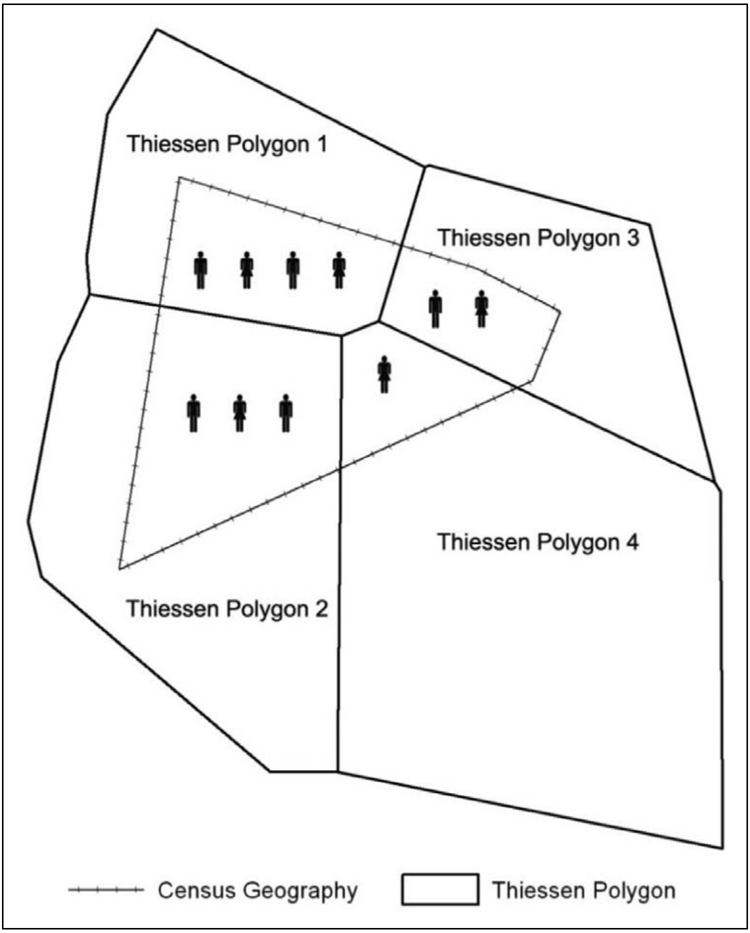

Figure 3. Uniform distribution of census data based on areal weighting technique. Figure 3 demonstrates the areal weighting technique used to distribute census data to Thiessen polygons. This hypothetical census geography contained ten people and falls within four Thiessen polygons: 40 percent (by area) falls within polygon 1, 30 percent within polygon 2, 10 percent within polygon 3, and 20 percent within polygon 4. Assuming an even distribution of people throughout the census geography it is extrapolated that 4 people will be in Thiessen 1, 3 people will be in Thiessen 2, 1 person in Thiessen 3, and 2 people within Thiessen 4. This process is repeated for all census geographies. Final values for the Thiessen polygon are computed by summing the values from the partial census areas falling within the Thiessen polygon.

Table 1. Crime Counts (2005-2006), Lagged Crime, and 2000 Census Demographics for Camden Corner Thiessen Polygons

$n = 1{,}751$	Type of Corner	Mean	Median	Minimum	Maximum	Standard Deviation
Count of violent crime	Non-Gang	1.57	1.00	0	34	2.74
	Dominated	3.53	2.50	0	25	4.01
	Diverse	5.63	3.00	0	44	6.93
	All	1.86	1.00	0	44	3.23
Count of property crime	Non-Gang	4.48	3.00	0	212	9.34
	Dominated	7.92	6.50	0	50	7.03
	Diverse	9.60	7.00	0	52	9.07
	All	5.23	3.00	0	212	9.27
Population	Non-Gang	44.80	35.26	0.85	464.67	41.69
	Dominated	50.65	43.79	2.18	246.30	36.51
	Diverse	57.54	43.96	2.92	340.91	48.30
	All	45.67	36.16	0.85	464.67	41.73
Spatial Lag (Violent)[a]	Non-Gang	−0.05	−0.05	−2.17	1.92	1.00
	Dominated	0.25	0.25	−1.52	1.51	0.76
	Diverse	0.86	1.20	−1.29	1.88	0.76
	All	0.00	−0.00	−2.17	1.92	1.00
Spatial Lag (Property)[a]	Non-Gang	−0.05	−0.15	−1.88	2.54	1.01
	Dominated	0.17	0.18	−1.38	1.40	0.70
	Diverse	0.75	1.00	−1.24	1.77	0.74
	All	0.00	−0.10	−1.98	2.54	1.00
% Fem. Headed HH	Non-Gang	0.17	0.16	0.08	0.32	0.04
	Dominated	0.17	0.17	0.10	0.26	0.04
	Diverse	0.16	0.15	0.11	0.32	0.04
	All	0.17	0.16	0.08	0.32	0.04
% Unemployed	Non-Gang	0.08	0.07	0.00	0.21	0.04
	Dominated	0.09	0.09	0.00	0.21	0.04
	Diverse	0.09	0.08	0.00	0.17	0.04
	All	0.08	0.07	0.00	0.21	0.04
% Better than HS Ed.	Non-Gang	0.22	0.21	0.08	0.54	0.09
	Dominated	0.19	0.19	0.08	0.42	0.08
	Diverse	0.19	0.21	0.08	0.37	0.08
	All	0.22	0.21	0.08	0.54	0.09
Status Index[b]	Non-Gang	0.01	0.04	−2.77	1.97	0.89
	Dominated	−0.10	0.03	−2.29	1.29	0.67
	Diverse	−0.07	0.12	−2.77	0.97	0.61
	All	0.00	0.43	−2.77	1.97	0.87

(continued)

Table 1 (continued)

$n = 1{,}751$	Type of Corner	Mean	Median	Minimum	Maximum	Standard Deviation
Race Index[b]	Non-Gang	0.03	0.17	−1.99	2.16	0.95
	Dominated	−0.23	−0.43	−1.99	1.90	1.18
	Diverse	−0.35	−0.18	−1.91	1.75	0.98
	All	0.00	0.12	−1.99	2.16	0.97
Foreign born Index[b]	Non-Gang	0.01	−0.28	−0.97	4.03	0.94
	Dominated	−0.20	−0.47	−0.96	2.73	0.78
	Diverse	0.12	−0.21	−0.93	1.81	0.88
	All	0.00	−0.30	−0.97	4.03	0.93
% Tenure < 5 Years	Non-Gang	0.43	0.43	0.15	0.80	0.13
	Dominated	0.43	0.42	0.15	0.74	0.10
	Diverse	0.44	0.46	0.15	0.59	0.09
	All	0.43	0.43	0.15	0.80	0.12
Young children[b]	Non-Gang	−0.02	0.06	−2.70	1.85	0.84
	Dominated	0.18	0.18	−2.06	1.72	0.65
	Diverse	0.08	0.35	−2.70	1.72	0.80
	All	0.00	0.87	−2.70	1.85	0.83

Note: Crime data from January 1, 2005, through December 31, 2006. There were 1,751 corners considered in this analysis. The spatial lag variables for both violent and property crimes were calculated using a two-stage least squares methodology. Demographic variables (population, percent female headed household, percent unemployment, percent with better than high school education, status, race, foreign born, percent tenure less than five years, and percent of young children) for the Thiessen polygons were created from reconfigured 2000 Census data.
[a] Lag values were created from standardized residual values generated during an OLS regression, hence the normal distribution and symmetry around the mean. See Methods section for more detailed review of the methodology utilized to create this variable.
[b] Scale comprised of variables that were z-scored.

Analytical Approach

Negative binomial regression models were used because of overdispersion in violent crime ($G^2 = 2353.49$, $p < .001$) and property crime ($G^2 = 7897.51$, $p < .001$; Long and Freese 2006; StataCorp. 2006). Four separate models were completed. Model 1 included two control variables: population[6] and the spatial lag variable. These variables were included in all models. Model 2 added two dummy variables capturing gang status of the corner. These two variables represented the unique effects of being a gang-dominated, or gang-diverse corner, relative to a non-gang corner. Model 2 captured the impacts of corner gang status on corner crime without taking into consideration the demographic fabric of the area.

Model 3 looked at the effects of social demographics on crime without consideration for the corner's gang status. It provided an estimate of the gross influence of community sociodemographic factors on the outcome. Model 4 combined both social demographics and gang corner status, identifying the effect of corner status while controlling for relevant social demographic characteristics. It provided estimates of net impacts of both corner gang status and sociodemographic factors. Since gangs are more likely in some locations than others, and/or gang corner markets are more tolerated in some locations than others, in a cross-sectional model gang variables may partially mediate sociodemographic impacts; therefore, gang variables may have smaller impacts in Model 4 as compared to Model 2.

These analyses were conducted with two correlated dependent variables (violent crime and property crime, Kendall's Tau-b = .537, $p < .001$). To minimize the risk of alpha inflation (Krathwohl 2004) due to multiple correlated dependent variables an adjusted alpha level, frequently referred to as a Bonferroni correction of $p < .025$ was adopted (see Perneger 1998).

Results

Parameters are presented as incident rate ratios (IRR), given their simple interpretation. An IRR of 2.0 suggests a one-unit change in the independent variable would be expected to increase the average predicted count on an outcome by a factor of 2.0, while holding all other independent variables constant. Conversely, an IRR of .50 would indicate that a one-unit change in the independent variable would be expected to decrease the average predicted count on the dependent variable by a factor of .50, while holding all other independent variables constant. IRRs range from 0 to infinity.[7]

Violent Crime

Gang impacts. Compared to corners with no drug gang affiliation, more violent crime occurred around gang drug dealing corners (Table 2; model 2). On average, before controlling for sociodemographic characteristics of the surrounding locale, the expected violent crime count on a single gang dominated open-air drug dealing corner was about double the expected count on a non-gang corner (IRR = 2.03; UCL: 2.63; LCL: 1.56; $p < .001$).[8] Further, if the gang corner was diverse, the expected average crime count was between two and three times larger than the expected count on a non-gang corner (IRR = 2.72; UCL: 3.76; LCL: 1.97; $p < .001$). The elevating effects of being either a single or multi-gang corner were basically

Table 2. Negative Binomial Regression Models of Violent Crime Counts at Corners

	Model 1		Model 2		Model 3		Model 4	
Violent Crime Count	*B* (*SE*)	IRR	*B* (*SE*)	IRR	*B* (*SE*)	IRR	*B* (*SE*)	IRR
Population	0.006 (0.001)***	1.006	0.005 (0.001)***	1.005	0.005 (0.001)***	1.005	0.005 (0.001)***	1.004
Spatial Lag	0.295 (0.034)***	1.343	0.219 (0.034)***	1.245	0.295 (0.040)***	1.343	0.204 (0.042)***	1.226
Dominated Dummy	—	—	0.708 (0.134)***	2.029	—	—	0.719 (0.134)***	2.052
Diverse Dummy	—	—	1.002 (0.164)***	2.724	—	—	0.987 (0.168)***	2.683
% Fem. Headed HH	—	—	—	—	−0.042 (0.050)	0.959	−0.046 (0.048)	0.955
% Unemployed	—	—	—	—	0.093 (0.044)†	1.098	0.097 (0.044)†	1.102
% Better than HS Ed.	—	—	—	—	0.005 (0.052)	1.005	0.042 (0.050)	1.043
Status Index	—	—	—	—	−0.112 (0.064)	0.894	−0.131 (0.062)†	0.876
Race Index	—	—	—	—	0.032 (0.051)	1.032	0.070 (0.050)	1.073
Foreign born Index	—	—	—	—	0.075 (0.047)	1.077	0.084 (0.046)	1.087
% Tenure < 5 Years	—	—	—	—	0.126 (0.040)**	1.135	0.099 (0.039)**	1.103
Young children	—	—	—	—	0.098 (0.531)	1.103	0.092 (0.052)	1.097
Pseudo-R^2	0.017***		0.027***		0.020***		0.030***	

Note: Negative binomial regression conducted on the number of crimes surrounding street corners in the City of Camden, NJ. Crime was aggregated to the closest street corner through the use of Thiessen Polygons. Street corners ($n = 1{,}751$) were classified as Non-gang ($n = 1{,}571$), Dominated ($n = 110$), or Diverse ($n = 70$). Indices were created to represent Status (median household income and median home value), Race (percent African American and percent Hispanic), Foreign Born (percent foreign born and percent race other than White, African American, or Hispanic), and Young Children (percent age 0-5 and percent age 6-12).

† $p < .05$.

** $p < .01$.

*** $p < .001$.

unchanged after controlling for features of community (model 4). If a corner was part of a gang's set space used for open-air drug distribution, more violent crime was occurring in the vicinity. If more than one gang sought to use the corner for distribution, even more crime was expected.

Community fabric. Instability had a significant positive impact ($p < .01$), and two status variables demonstrated marginal ($p < .05$; model 4) impacts on violent crime counts. Each percentage increase in residents with tenure less than five years increased the expected average count of violent crime by about 10 percent (IRR = 1.10; UCL: 1.19, LCL: 1.02). Counts were slightly higher in locales with higher unemployment rates (IRR = 1.10; UCL: 1.20; LCL: 1.01) and slightly lower in locales with higher socioeconomic status (IRR = .88; UCL: 0.99; LCL: 0.78). Stability has not been found to be the strongest demographic correlate of community crime rates (Pratt and Cullen 2005), with status and race often found to be more powerful. At this lower level of analysis, however, when focusing on micro-ecologies rather than ecologies (Taylor 1997), instability linked to more violent crime, even after controlling for gang-related drug activities.

Spatial lag. Violent crime counts on corners were substantially influenced by nearby violent crime. Each standard deviation increase in the instrumented lag variable increased the expected violent crime count on a corner by about 23 percent (IRR = 1.23; UCL: 1.33; LCL: 1.13; $p < .001$; model 4). Given the small geographies under analysis, this is not surprising.

Property Crime

Gang impacts. The relationship between gang corners and property crime were similar to those found for violent crime (Table 3). On average, before controlling for sociodemographic characteristics, the expected property crime count of corners controlled by a single gang was about 54 percent higher than non-gang corners (IRR = 1.54; UCL: 1.94; LCL: 1.22; $p < .001$; model 2). The expected average crime count for diverse corners was slightly higher with an expected increase of 63 percent over non-gang corners (IRR = 1.63; UCL: 2.18; LCL: 1.22; $p < .001$; model 2). Comparisons between model 2 and model 4 show very little change in the impact of either gang variable after controlling for sociodemographics. Although gang open-air drug distribution linked to higher property crime counts as it did with violent crime counts, for property crime counts gang-dominated and gang-diverse corners had about the same impact.

Table 3. Negative Binomial Regression Models of Property Crime Counts at Corners

	Model 1		Model 2		Model 3		Model 4	
Property Crime Count	*B* (*SE*)	IRR	*B* (*SE*)	IRR	*B* (*SE*)	IRR	*B* (*SE*)	IRR
Population	0.007 (0.001)***	1.007	0.007 (0.001)***	1.007	0.007 (0.001)***	1.007	0.007 (0.001)***	1.007
Spatial Lag	0.180 (0.028)***	1.197	0.156 (0.028)***	1.169	0.162 (0.352)***	1.176	0.128 (0.036)***	1.136
Dominated Dummy	—	—	0.429 (0.119)***	1.535	—	—	0.452 (0.119)***	1.571
Diverse Dummy	—	—	0.491 (0.148)***	1.633	—	—	0.483 (0.151)***	1.621
% Fem. Headed HH	—	—	—	—	−0.032 (0.041)	0.969	−0.034 (0.041)	0.966
% Unemployed	—	—	—	—	0.068 (0.037)	1.070	0.066 (0.037)	1.068
% Better than HS Ed.	—	—	—	—	−0.045 (0.043)	0.956	−0.025 (0.043)	0.975
Status Index	—	—	—	—	−0.081 (0.053)	0.923	−0.093 (0.053)	0.912
Race Index	—	—	—	—	0.037 (0.042)	1.037	0.055 (0.042)	1.056
Foreign born Index	—	—	—	—	0.036 (0.039)	1.037	0.043 (0.038)	1.044
% Tenure < 5 Years	—	—	—	—	0.155 (0.034)***	1.167	0.147 (0.033)***	1.158
Young children	—	—	—	—	−0.056 (0.045)	0.945	−0.064 (0.044)	0.938
Pseudo-R^2	0.013***		0.016***		0.016***		0.019***	

Note: Street corners ($n = 1{,}751$) were classified as Non-gang ($n = 1{,}571$), Dominated ($n = 110$), or Diverse ($n = 70$).
*** $p < .001$.

Community fabric. Instability had a significant positive impact on property crime. The expected property crime level was 16% higher in corners where all residents had arrived in the last five years versus corners where none had arrived during that time. (IRR = 1.16; UCL: 1.24, LCL: 1.08; $p < 0.001$; model 4). Again, at this level of geography for property crime, as with the violent crime counts, stability proved to be more important than the more typical crime–community correlates of status and race.

Spatial lag. Property crime counts were strongly influenced by the level of property crime in surrounding areas. Each standard deviation increase in the instrumental lag variable increased the expected property crime count of a corner by about 14 percent (IRR = 1.14; UCL: 1.22; LCL: 1.06; $p < .001$; model 4). Again, given the small geographic units of analysis, this was not surprising.

Discussion

Significantly higher violent and property crime counts were found around the portion of gang set space—the corners—used for open-air drug distribution. When looking at violent crime, the criminogenic effect was substantially larger if more than one gang included the corner in their respective set space for distribution. Both violent and property crime corner drug dealing links persisted net of fundamental features of community demographic fabric and net of surrounding crime levels. This relationship was not dependent upon choosing either population or area as the relevant control variable. Models using area (results not shown) were consistent with those presented here. Not only was the gang influence independent of community fabric, the IRRs for the two gang variables were largely unaffected by the inclusion of sociodemographic variables. This would suggest that the processes whereby gang-drug corners influenced localized crime counts may have acted independently of the underlying social demographic factors.

Tita and Ridgeway (2007) found gang set space at the census block group level linked significantly to calls for gun assaults and calls for drug crimes. The current investigation focused on just that portion of the set space used for open-air drug distribution, and used a different spatial level of analysis, focusing on corners rather than census block groups. At this level of analysis and for this type of gang set space, there is a strong connection with both violent and property crime. Whether the different relationship observed in Camden (NJ) as compared to Pittsburgh (PA) depended on the level of analysis, or the focus on just one key element in gang set space, or the use of reported crime rather than calls for service, or the different locations and time periods remains an important and open question. But at the least it appears that different types of positive drug gang set space–crime linkages may surface. This research further extends earlier findings by suggesting that, at least for violent crimes, corners where gangs compete to distribute drugs experience more crime than corners where one gang is established. Whether the higher violence is a side effect of competition or intimidation attempts on the part of gang members or a reflection of more desirable corner markets with higher foot traffic levels is not known. Again, longitudinal work documenting shifts in violence as gangs move into and out of particular corner markets may prove informative.

Turning to features of community structure, current results showed that only one element linked consistently to both violent and property crime; the percentage of individuals who had lived there for less than five years connected positively to more crime. This is consistent with previous research that has linked instability to drug use (Freisthler et al. 2005), homicide (Kubrin 2003), and juvenile violence (Osgood and Chambers 2000). Attributing this finding to any particular criminological theory must be undertaken with caution. It has been argued before that community instability impairs local supervisory control (Bursik and Grasmick 1993; Shaw and McKay 1942). That may be true; but any element of community demographic fabric can link to a wide array of potentially relevant local processes. Thus, we think it is wiser to leave the specification of the relevant mediating processes as an important avenue for future inquiry.

Turning to spatial dependency, the spatial lag term captured both unmeasured variables and the spatial distribution of crime and corrected for spatially auto-correlated errors. Its inclusion confirms that the impacts of the other predictors are endogenous. Significance of the lag term suggests relevant location-based, resident-based, gang-based, or agency-based dynamics not captured by the current predictors. Since the geographies used here are quite small, the dependencies could arise from movement of the same individuals or same gangs across several nearby corners. The extent to which the spatial dependency arises from agent-based dynamics linked to individuals or individual gangs, or patterns laid down as part of the urban fabric, or agency predilections for responding certain ways in certain parts of the city, has important implications for both theory and prevention concerns. Furthermore, the use of small highly localized geographies may have had an impact upon how the demographic variables connected to crime (Openshaw 1984a; Openshaw and Taylor 1979; Yule and Kendall 1950).

The unknown impact of areal aggregation becomes an empirical external validity question to be taken up in future work.

These findings reinforce a substantial body of literature suggesting that crime clusters at relatively few locations and that the land use underlying these locations plays an important role in understanding the spatial distribution of crime. Therefore, these findings suggest that crime prevention strategies may be better off targeting specific locations instead of specific people or groups. Furthermore, the results suggest that areas associated with multiple gangs are related to a greater level of crime. Focusing law enforcement resources upon a single gang would likely result in an increased number of multi-gang corners. Instead, resources would be better directed toward location denial strategies. These efforts would exclude or prevent gangs from operating within targeted areas. Location denial strategies must be sensitive to organizational, community, and financial concerns. These initiatives often come under fire because of the belief that crime will simply move to nearby locations. Empirical research in this field fails to support this claim. On the contrary, several studies have found a diffusion of benefits; areas surrounding places of police focus often see reductions in crime (Clarke and Weisburd 1994; Painter and Farrington 1999; Weisburd et al. 2006).

Location denial strategies also come in the form of civil gang injunctions. Injunctions usually prohibit specifically named individuals from engaging in certain behaviors in explicitly defined locations. Injunctions can prohibit specific behaviors and activities or completely exclude a person from utilizing a public space. Evaluative research is limited but promising. Grogger (2002) found a 5 to 10 percent crime reduction in injunction areas. This crime reduction was driven primarily by a reduction in assaults. Research by Maxson and colleagues (2005) suggested that injunctions had positive impacts upon target communities. Short-term impacts included less gang presence, fewer reports of gang intimidation, and less fear of confrontation with gang members. Long-term impacts, however, were less positive. No significant change was found for social cohesion, informal social control, collective efficacy, or willingness to call the police (Maxson, Hennigan, and Sloane 2005). Rough estimates of cost effectiveness suggest that the crime reduction impact of the injunction outweighs the cost of implementation and enforcement (Grogger 2005). Although more research in this area is needed, civil gang injunctions provide an optimistic avenue for reducing the impact of gangs.

Although the methodology used here determines crime differences surrounding different types of corners, it is unable to ascertain causal ordering between crime and gang drug-corner status. It is not possible to determine if the gang-drug markets are driving the crime in the surrounding area or, alternatively, if these gang drug-distribution sites are setting up in areas with already high levels of crime. The reality of the situation is that a combination of both views is the most likely explanation. Areas where informal social controls are weak may draw in serious offenders (Wilson and Kelling 1982). Drug markets may then develop in these areas thereby further weakening the already low levels of social cohesion. Tita and Ridgeway (2007) find support for the hypothesis that gangs establish set space in areas where crime is already high. After the establishment of the gang set space, certain types of crime became even higher still. The research findings here are consistent with, if not necessarily in direct support of, this proposition.

Although this analysis does not include known criminogenic facilities such as alcohol outlets (Roncek and Bell 1981; Roncek and Maier 1991), nodes of public transportation such as bus, subway, and train stops (Block and Block 2000; La Vigne 1996; Loukaitou-Sideris, Liggett, and Iseki 2002), and, more generally, commercial land use (Kinney et al. 2008), the inclusion of a spatial lag term does ameliorate some of the potential spatial bias generated by these locations. Future studies should attempt to control for the influence of these and other potentially criminogenic land uses in an effort to more clearly disentangle the effects of demographics, land use, and gang set space corners.

Two limitations are inherent: the spatial–temporal relationship between gang-drug corners and crime. First, it could not be determined if a crime was associated with the gang-drug location. Crimes could be assigned to gang-drug corners even without gang involvement or an incident related to drug dealing activity (the spatial limitation). It was assumed that a crime was related to the corner to which it was closest. Second, it was not known if crime events took place during hours when drug sales were occurring (the temporal limitation). Different corners were "open" as drug markets for different periods and time slices. These limitations notwithstanding, the results are unambiguous with regard to the relationship between gang corners and crime.

While the demographics of Camden prevent a broad extrapolation, these findings still provide important information for future research. The results identified the importance of considering sociodemographic fabric even when analyzing micro-space geographies. Furthermore, this study contributes to the literature by utilizing an innovative approach (Thiessen polygons) to combining crime data, demographic data, and criminal intelligence information. While Camden differs from many cities, the implications of this study may still be applicable to a wider audience. Location denial strategies have the potential to work in a variety of situations where small geographic areas have a high concentration of crime.

One final limitation is worth discussing, linked to the well-known limitations of police recorded data generally. If the locations of the gang-drug corners were incorrect, the conclusions drawn from this analysis would be suspect. In Camden, the Office of Intelligence Services determined these locations from a number of different sources including offender self-reports and officer observations. Research into the veracity of offender self-reports is promising. For example, Webb, Katz, and Decker (2006) found drug user's self-reports to be valid measures of actual drug use. Although in no way conclusive, this provides some support for the assumption that the data utilized here are accurate. This data set also utilized patrol officer observations in order to determine the location of gang-drug markets. It is possible to argue that officers are more likely to be in high crime areas and, therefore, are more likely to see gang members dealing drugs in those locations. Because of this gang drug dealing set space in lower crime locations may have been systematically missed. It is difficult to fault this criticism. Fortunately, even if this criticism is correct, and the control group was contaminated by "missed" gang corners, then the results here provide a *conservative* estimate of the impact of gang set space for drug dealing around corners. Beyond this ability to interpret the results conservatively, we acknowledge the limitation of working with data that are recorded by officers volunteering information to a specialized collection regime instigated by the Office of Intelligence Services.

Conclusion

This analysis provided a conceptual refinement of drug gang set space by looking at one type of the set space—where they distribute drugs in small open-air, corner-based markets, and used an areal aggregation consistent with what is known about these gang activities. No evidence was found supporting the claim that drug groups reduce the level of crime around the space used for open-air drug distribution. Rather, gang drug dealing sites were associated with substantially higher violent and property crime especially, in the case of violent crime, when multiple gangs were associated with the corner. These links were endogenous and net of demographic crime correlates. The nature of the drug distribution location link to crime is different than has been previously seen for the general gang set space—crime link. When the focus is on crime surrounding known drug corners in a core city of a large metropolitan area, the most important determinant of both violent and property crimes is not the surrounding sociodemographics fabric but whether it is drug dealing location and whether the control of that set space is unquestioned or between a diverse group of gangs.

Authors' Note

Portions of an earlier version of this article were presented at the National Institute of Justice (NIJ) Ninth Crime Mapping Research Conference, 2007, Pittsburgh, Pennsylvania. Opinions stated here are solely the authors' and do not necessarily reflect the opinions of Temple University or the various grant-awarding bodies. The authors would like to thank Elizabeth Groff, Eric McCord, George Rengert, Christopher Salvatore, and Brian Wyant for helpful and insightful comments on earlier drafts and the Camden Police Department and the Camden County Prosecutor for data access.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interests with respect to the authorship and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research and/or authorship of this article: This research was largely made possible by funding provided through the Summer Research Opportunities Program (SROP) of the Alliance for Graduate Education and the Professoriate at the Temple University Graduate School. This project was supported by Award No. 2006-DJ-BX-0023 awarded by the Bureau of Justice Assistance, Office of Justice Programs.

Notes

1. Some might be concerned about selecting corners throughout the entire city for a comparison group and argue that many areas would be too far away and thus non-comparable to the drug dealing locations. Readers should consider that drug dealing locations are geographically dispersed and Camden is a small city. This can be demonstrated by two additional analyses conducted. First, a simple proximity analysis demonstrated that 98.9 percent of control corners fall within 0.5 miles (2,640 feet) of a drug dealing location (either single gang or disputed corners). Further analysis demonstrated that 73.2 percent of corners were within 1,000 feet of a drug dealing location. An analysis (model 4) using only the control corners within 1,000 feet of a dominated or disputed corner showed only slight

differences compared to the results presented here. No demographic variables attained statistical significance. Both the dominated dummy and the disputed dummy variables remained significant, strong predictors of crime. Finally, both population and the spatial lag remained significant, and in the same direction as the models reported. Had the comparison group been restricted to corners located within 1,000 feet of a known drug distribution set space location, the results would have been substantively the same.

2. The method of coding the gang status dummy variable allows for partialing out the effects of the dominated and disputed corners. It is important to recognize that these two variables captured the unique influence of the two gang types because each is compared to the reference string of non-gang corners. This can be demonstrated with a simple exercise. In a regression analysis with only the two dummy variables and violent crime as the outcome, the incident rate ratios were 2.24 and 3.57 for the dominated and disputed dummies, respectively. The mean violent crime counts for each group were as follows: non-gang = 1.57, dominated = 3.53, and diverse = 5.63. These values produce a mean ratio of 2.24 (mean of single gang/mean of non-gang) and 3.58 (mean of disputed gang/mean of non-gang). These values coincide with the values produced from regression analysis thus confirming the interpretation of the IRRs presented in this section as correct.
3. The hit rate refers to the percentage of addresses accurately mapped. Geocoding match options were set to the following: spelling sensitivity = 80; minimum candidate score = 10; and minimum match score = 60. Monte Carlo simulations of degrading hit rates suggest that matching rates in excess of 85 percent appear to be adequate (Ratcliffe 2004). No noticeable recurring patterns were found among the missing data and their omission from further analysis would not significantly affect the findings of this study.
4. This process required a slightly different procedure for census variables that could not be distributed across the census geography. In the analysis conducted here, these variables were median home value and median income. Instead of multiplying by the percentage of the area within the census geography, it was necessary to multiply by the percentage of the Thiessen polygon that was occupied by the NGU. When the values of the NGU are summed, they provided the Thiessen polygon with a value that represented the weighted median home value or median income.
5. The generalized clean instrument for the violent crime spatial lag model was comprised of police sector dummy variables representing eight unique police sectors, median year the structures were built, percentage of households with five or more rooms, percentage of people living in family households, percentage of households occupied by three or more people, a dummy variable for commercial land use, and the x-centroid of the Thiessen polygon. The *R*-squared for the

regression model was .631. The clean instrument for the property crime lag variable included all of the abovementioned variables in addition to percentage of people with commute time less than 30 minutes and y-centroid of the Thiessen polygon. The R-squared for the regression model was .590.

6. Another possibility would be to use area instead of population as a control variable. Models 1 through 4 were repeated for both violent and property crime with area instead of population as the control variable (results not shown). For violent crime, size of the polygon was not significantly related to the count of crime events. No other differences were found between population models and area models for violent crime. Unemployment and tenure were significant and in the same direction as was the spatial lag term. The gang status dummy variables were both significant and had largely the same IRR values (dominated dummy-population model = 2.052, area model = 2.109; disputed dummy-population model = 2.683, area model = 2.851). This consistency was also found for property crime. Demographic controls remained largely unchanged save for the percent unemployed, which attained marginal significance in the area models. Once again the coefficients for the gang status dummy variables were virtually unchanged (dominated dummy-population model = 1.571, area model = 1.680; disputed dummy-population model = 1.621, area model = 1.791). The debate between area versus population as a control has no impact over the substantive conclusions that can be drawn from this analysis.
7. Stata calculates incident rate ratios are calculated as $\beta = \log(\mu_x{+}1/\mu_x)$, where β is the regression coefficient and μ_x is the expected value of the predictor x. The notation $x{+}1$ references a one-unit change in the predictor variable x (Long and Freese 2006).
8. LCL and UCL refer to the 95 percent lower and upper confidence interval. Confidence intervals are not symmetric around the incident rate ratios. This results from converting regression coefficients to IRRs. Stata computes 95 percent confidence intervals using the delta method that does indeed generate upper and lower bounds that are symmetric around the coefficient (Xu and Long 2005). Converting between coefficients and IRRs is done through exponentiation of the coefficient (Long and Freese 2006). Because exponentiation is a nonlinear transformation, asymmetric UCL and LCL values are generated.

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