Chapter 7
Crime, Neighborhoods, and Units of Analysis: Putting Space in Its Place

George E. Tita and Robert T. Greenbaum

Abstract Research has long established that crime is not randomly distributed, and spatial regression models of crime have clearly demonstrated that crime patterns cannot be explained merely by the socio-economic characteristics of a particular place. These findings are a reminder that "space matters" and that neighborhoods are not analytically independent units. Modeling the clustering of crime through spatial regression requires two important decisions. First, one must choose a unit of analysis that is consistent with the social processes believed to be driving the observed patterns. Second, one must consider the relationships among these units such that the model captures the influence the activities in other areas have on outcomes in the neighborhood. Within criminology, this second feature has been given insufficient consideration. Instead, the connectedness of spatial units has been taken as given and modeled solely through adjacency or a distance decay function. This chapter critiques such inductive approaches used to model and explain the spatial distribution of crime. Drawing upon the modeling of network autocorrelation within the social influence literature, we describe a deductive approach wherein specific social processes are posited, measured and modeled a priori. An empirical example using gang violence demonstrates this deductive approach and we find that the spatial distribution of violence is influenced by neighbors defined by the socio-spatial dimensions of gang rivalries rather than simply by geographically contiguous neighbors. We emphasize that a complete discussion of the appropriate unit of analysis must also consider the spatial dimensions of the social phenomena thought to be responsible for the spatial patterning.

Introduction

When examining the appropriate unit of analysis in crime research or any other examination of a social process, it is important to properly account for all of the influences that affect activity within that unit. Regardless of the choice of

G.E. Tita
Department of Criminology, Law and Society, University of California – Irvine, CA, USA
e-mail: gtita@uci.edu

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neighborhoods, census tracts, policing districts, or some other areal units, social processes are typically influenced by actions, events, and conditions in “neighboring” spatial units in addition to the characteristics that define the focal unit. Thus, in order to understand and model these processes, it is imperative that we properly capture how these processes play out across the geography of a study region.

We begin this chapter by providing an overview of spatial studies of violence. We move quickly into a comparison between the primarily inductive modeling approach popularized within criminology with the more deductive approach used in more general studies of social influence. The goal of these first two sections is to lay the foundation for our argument that by using theory coupled with empirical evidence, it is possible to specify a spatial autocorrelation matrix that better approximates the social mechanism responsible for explaining the observable spatial patterns of crime.

Over the past decade, there has been a considerable increase in the number of published studies that explore the spatial distribution of violent crime. Much of this was fueled by the unprecedented growth in levels of youth homicide during the late 1980s through the early 1990s. Studies at the national level (Blumstein and Rosenfeld 1998; Cork 1999), the county level (Baller et al. 2001; Messner and Anselin 2004), and the local level (Cohen and Tita 1999; Morenoff et al. 2001; Griffiths and Chavez 2004) have consistently demonstrated two things. First, the subpopulation at greatest risk of homicide victimization is comprised of young urban minority males. Second, homicides exhibit a non-random pattern of positive spatial concentration, meaning that areas with similar levels of violence cluster in space. Furthermore, the concentration of high violence areas typically occur within disadvantaged urban communities.

Ecological studies of crime have clearly demonstrated that the spatial patterning of crimes can not be explained by the socio-economic characteristics of place alone. Instead, the spatial analysis of crime literature suggests that concentrations of crime are the result of particular social processes or mechanisms that are manifest in such a way that crimes in one location influence the levels and patterns of crimes in nearby or “connected” places. To date, the primary value of these studies has been to serve as a constant reminder that “space matters,” thereby refuting the notion that neighborhoods, however defined, are analytically independent and that ecological models of crime need to consider the ways in which the observable outcomes in one neighborhood are dependent upon the actions and activities occurring in other areas (Sampson 2004; Morenoff et al. 2001). However, though many plausible explanations have been offered, the empirical findings offer little in the way of supporting definitive statements on the exact nature of the processes that influence crime patterns across space.

The inductive modeling strategy employed in most studies is part of the reason why the nature of the social processes responsible for relationships among crimes across space remains conjecture. Typically, the researcher takes an outcome of interest, aggregates the outcome and explanatory variables to the most conveniently available areal unit of analysis, assumes that events in only spatially adjacent areas can influence one another, estimates a non-spatial model to “test for” a particular functional form of spatial influence, and then, based upon a set of diagnostic tests, picks the appropriate statistical model. If the coefficient on the spatial term is statistically significant, ex-post explanations are constructed regarding the "importance of space." The most frequent interpretations include those social processes related to contagion (Loftin 1986), exposure (Morenoff et al. 2001; Griffiths and Chavez 2004), gangs (Morenoff and Sampson 1997; Rosenfeld et al. 1999; Cohen and Tita 1999; Griffiths and Chavez 2004), and drug markets (Morenoff and Sampson 1997; Cork 1999; Tita and Cohen 2004).

This differs from the deductive modeling approach employed in the field of social network analysis. The social networks literature recognizes both spatial regression analysis and network autocorrelation models as members of the family of models known more generally as "social influence models" (Marsden and Friedkin 1994; Leenders 2002). As the name suggests, social influence models provide a conceptual and analytical framework for exploring the structural processes by which people, organizations, or places are influenced by others. In modeling processes of social influence within the network literature, one starts with a very clear idea of the process (or processes) by which influence occurs across units of analysis, ensures that these units are linked in accordance to the pre-specified processes (e.g., geographic adjacency, status, or social similarity), estimates the appropriate statistical model, and then conducts hypotheses tests to determine whether the initial beliefs regarding influence processes are empirically supported.

In the following pages, we explore what it would mean to employ such a deductive approach to the spatial modeling of crime. We begin with a more thorough treatment of the two most important choices made in specifying both network autocorrelation and spatial autocorrelation models – choosing the appropriate unit of analysis and linking these units in a theoretically or empirically justified manner so as to be consistent with an *ex-ante* specified process. We also include a discussion of the differences between spatial error and spatial dependence/lag models. Next, we review the commonly offered interpretations in light of theoretical and empirical evidence guiding these principles. We conclude with an empirical example to demonstrate the validity of our approach. The intent of the exercise is not to answer a particular policy question. Instead, the primary question is whether additional insights can be gained by moving beyond typically employed spatial adjacency to explicitly consider the socio-spatial dimensions of social processes. Using gang-involved gun violence, we demonstrate how different specifications of the spatial autocorrelation matrix (also referred to as the spatial weights matrix) lead us to conclude that gangs do influence levels of violence in other areas but that the extent of the influence extends beyond simple geographic contiguity.

The Network and Spatial Approaches to Modeling Influence

Models of spatial autocorrelation share a number of common features with network autocorrelation models. Substantively, they both explore similar questions pertaining to influence and contagion effects, albeit among different units of observations.[1] These approaches also assume that proximity or connectedness facilitates the flow

[1] See Marsden and Friedkin (1994) for examples.

of information or influence across nodes in a network or across geographic space. Individuals, organizations, or places are more likely to be influenced by the actions, behaviors, or beliefs of others who are "closer," meaning observations that share either geographical or social proximity, or similarity in "status" are given the most weight in the model. Methodologically, the lack of independence among geographical units is identical in its content and construct to the interdependence inherent among the actors in a social network. The lack of independence among observations is more than a statistical nuisance that precludes one from employing standard Ordinary Least Squares (OLS) regression analysis.[2] Instead, the interdependence is at the core of our attempts to understand how links among observations matter.

Marsden and Friedkin (1994) identify three important challenges researchers face in utilizing the network approach to models of social influence. These include: (1) articulating the *substantive process* through which influence occurs, (2) correctly specifying an autocorrelation matrix, and (3) estimating the correct statistical model. After discussing these below, we compare the social network/social influence approach with the manner in which these issues are dealt with within the criminology literature.

Those interested in the adoption of innovations or beliefs differentiate between processes of communication/structural cohesion and processes of comparison/equivalence. Communication/structural cohesion presumes that influence occurs through a direct social tie, which may occur through a variety of means (e.g., face-to-face, electronic, or print media). Influence that occurs through processes of comparison or equivalence does not depend upon a formal tie among individuals. People recognize that they are part of a social system and then mimic the behaviors of others who occupy similar roles (i.e., are "equivalent") within the same social system. This sort of contagion through comparison is identical to the spatial process of "hierarchical diffusion" in which transmission occurs not along spatially contiguous geography, but rather along an ordered (often by status) route. Cliff et al. (1981, p. 9) note that hierarchical diffusion is "typified by the diffusion of innovations (such as new styles in women's fashions or new consumer good, for example television) from large metropolitan centers to remote villages."

The choice of theoretical/substantive process has direct bearing on the second challenge – the appropriate specification of the autocorrelation matrix, "W." Unfortunately, W cannot be estimated and must be specified *a priori*. This matrix is the most critical element in both network and spatial autocorrelation models, as it represents the dependence among observations in terms of the underlying social or geographic structure that explicitly links actors or geographic units with one another. As Leenders (2002, p. 26) notes:

> "W is supposed to represent the theory a researcher has about the structure of the influence processes in the network. Because any conclusion drawn on the basis of autocorrelation

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[2] However, if observations are merely correlated across space due to arbitrary political boundaries, this type of spatial autocorrelation should be modeled as a nuisance parameter by incorporating a spatial error term.

models is conditional upon the specification of W, the scarcity of attention and justification researchers pay to the chosen operationalization of W is striking and alarming. This is especially so, since different specifications of W typically lead to different empirical results".

In network models of influence, the existence of a tie between ego (one particular actor) and ego's alters (those who influence ego) is predicated upon defining the appropriate frame of reference. This step results in the specification of the actor by actor social network autocorrelation matrix (W), where each element $w_{i,j} = 1$ if i and j are tied to one another, else the cell $w_{i,j} = 0$. If friends are believed to populate the general frame of reference by which others are influenced, then $w_{i,j} = 1$, if and only if i and j are "friends." Similarly, if the frame of reference is based upon status, then $w_{i,j} = 1$, if and only if i and j share comparable levels of status attainment. Actors that belong to the same group (formal or informal) may also constitute a shared frame of reference.

The third and final step in the process requires one to choose the appropriate statistical model and assess its predictive power. Once again, the underlying substantive process guides this choice. As is the case with spatial models, the choice of models depends upon whether the process of influence operates through an autocorrelated error term or through network dependence (see Elffers 2003).

Autocorrelated error models account for the unobservable similarity or interdependence among units of analysis. When the error terms from a regression are not independent due to correlation across social or spatial units due to, for example, units of measurement that differ from the geographic scope of the phenomenon, OLS models that do not take into account the autocorrelated error term will still yield unbiased coefficients. However, estimates of the standard errors on those coefficients will be incorrect (Anselin 1988). To account for this autocorrelation among geographic units, *spatial error models*, which include spatially lagged error terms, can be estimated using maximum likelihood.[3]

If interdependence across actors or space is instead due to a particular social process, then this dependence is more appropriately modeled with a lagged dependent variable. Failure to include a lagged dependent variable in the model leads to omitted variable bias (Anselin 1988; Elffers 2003). A *spatial lag model* explicitly models the dependence or spillover across spatial units.[4]

The modeling of neighborhood effects within the criminological literature requires addressing the identical set of concerns. However, as noted in the

[3] $Y = X\beta + \varepsilon; \varepsilon = \lambda\, \varepsilon_c + u$, with $E[u] = 0$, $E[uu'] = \sigma^2 I$, where $\varepsilon = W\varepsilon$, and W is the $(N \times N)$ autocorrelation weighting matrix that contains information about which spatial units are considered to be neighbors. λ measures the spatial correlation of the error term. Note that if there is no correlation among neighbors' error terms, λ equals zero and the OLS estimators are BLUE. The same holds true when modeling unobserved similarity involving individuals, groups or organizations.

[4] $Y = \rho\, WY_s + X\beta + \varepsilon$; with $E[\varepsilon] = 0$, $E[\varepsilon\varepsilon'] = \sigma^2 I$, where ρ is the spatial coefficient on the lagged dependent variable, and it will be nonzero if outcomes in one location influence outcomes in another location.

introduction, criminologists tend to take more of an inductive, post hoc approach to specifying spatial models. While we have learned a great deal from the traditional approach, and each of the modeling concerns are typically addressed, they are not treated in the logical order dictated by a more careful, deductive approach. Rather than first specifying the social process, constructing the appropriate weights matrix, and then choosing the statistical method, spatial models of crime often first construct the weights matrix, choose the statistical model, and only then, in the presence of a statistically significant coefficient on the spatial term, are specific social processes considered.

The presence of positive spatial autocorrelation has been interpreted as evidence of unobserved social processes. This conclusion rests heavily upon the fact that the socio-economic composition of place (i.e., the correlated effect) fails to account for the spatial concentration of events. That is, even once factors such as race, poverty, and population density are accounted for, violence continues to exhibit spatial clustering. This remaining spatial clustering is most likely due to omitted measures of relevant neighborhood processes. While it is possible that some of these omitted variables are missing measures of local characteristics, it is more likely that the spatial clustering is due to the omission of variables that capture the influence of social processes across space.

Efforts to explain the social processes responsible for observed patterns of violence often focus on the contagious nature of violence and distinguish contagion that is driven by "exposure" versus contagion that is the result of "diffusion." Morenoff and his co-authors differentiate between the two processes by noting that diffusion "focuses on the consequences of crime as they are played out over time and space – crime in one neighborhood may be the cause of future crime in another neighborhood. The concept of exposure focuses on the antecedent conditions that foster crime, which are also spatially and temporally ordered" (Morenoff et al., 2001, p. 523).

There are two elements to exposure that researchers have considered when understanding how conditions in one neighborhood can influence levels of violence in other neighborhoods. First, violence in the focal neighborhood might be higher than predicted by structural characteristics, if it is "exposed" to offenders from other areas. The routine activities perspective (Cohen and Felson 1979; Messner and Tardiff 1986) suggests that the chances of victimization increases for those individuals living in close proximity to known offenders. In addition to offenders, crime in a focal neighborhood may by influenced by exposure to underlying criminogenic features in neighboring areas. Second, in one of the few studies that does employ a deductive modeling strategy, Mears and Bhati (2006) argue that social networks are unbounded by space and note that ties are often homophilous in terms of race, ethnicity, socio-economic status. Thus, behaviors in a focal area are presumed to be influenced by behaviors in socially similar areas because there is a higher probability of ties linking (i.e., exposing) similar areas.

In addition to processes of exposure, violence may diffuse from one area to another through various processes involving structured social interactions. Several such mechanisms have been posited. Loftin (1986) argues that the spatial concentration of assaultive violence and its contagious nature is the result of certain subcultural processes. He uses "subcultural" to refer to a process wherein violence spreads throughout the population as the result of direct social contact. Thus, an increase in violence can result in an epidemic when a small increase in assaults sets off a chain reaction of events causing local individuals to enact precautionary/protective measures in hopes of reducing their chances of victimization. At the extreme, individuals take pre-emptive actions (i.e., assault others) to protect against the possibility of being the victim of an assault, thereby feeding the epidemic. Loftin argues that the very existence of the moral and social networks that link individuals together within their local environment exacerbate the epidemic. "When violence occurs it draws multiple people into the conflict and spreads either the desire to retaliate or the need for preemptive violence through the network, potentially involving ever increasing numbers of individuals in the fight" (Loftin 1986, p. 555).

Alternatively, the notion of negative spatial autocorrelation is possible. That would imply that high crime in a neighborhood would lead to lower crime in nearby neighborhoods. For example, residents in a neighborhood spatially proximate to a high crime neighborhood might spend much more on safety or take other precautions than residents in a neighborhood with a very similar demographic composition that borders safer neighborhoods. Thus, by virtue of being proximate to a high crime neighborhood, this increased spending on crime prevention may lead to lower crime than is found in similar neighborhoods elsewhere.

Two of the most common mechanisms implicated in the literature as the source of spatial dependence include the dynamics of local drug markets and/or the presence of gang wars (e.g., Decker 1996; Wilkinson and Fagan 1996; Morenoff and Sampson 1997; Cohen et al. 1998; Cohen and Tita 1999; Rosenfeld et al. 1999; Morenoff et al. 2001; Griffiths and Chavez 2004; Tita and Cohen 2004). Several features of drug markets, especially crack cocaine, make them obvious candidates responsible for the diffusion of violence. First, guns quickly became important "tools of the trade" among urban youth dealing crack. As Blumstein (1995) hypothesized and empirically supported by Blumstein and Cork (1996), arming participants in crack markets increases the risks of violence for non-participants as well. Faced with increased risks to personal safety, youth outside crack markets increasingly carry guns and use them to settle interpersonal disputes, thereby spreading gun violence more broadly among the youth population. Second, drug markets often involve competition among rivals looking to increase their market share. Therefore, drug related murders are likely to be retaliatory in nature.

As Decker (1996) notes, there are important features that define gangs which also make them effective agents of diffusion. First, they are geographically oriented. The turf or "set space" where urban street gangs come together is a well-defined, sub-neighborhood area that remains consistent over time (Klein 1995; Moore 1991; Tita et al. 2005). Second, urban street gangs are committed to the defense of their turf. Thus, gang violence is inherently retaliatory in nature, which should promote predictable temporal and spatial tit-for-tat ordering of violence.

The above explanations where reached inductively after first producing a statistically significant coefficient on a spatial dependence term, which itself was derived primarily out of convenience (spatial contiguity). Therefore, Leender's advice that different social processes lead to different specifications of *W* is generally ignored. This is problematic on several fronts.

First, it assumes that the processes of exposure and diffusion operate over the same geographic dimensions and that the same unit of analysis is appropriate for both. This remains an empirical question that spatial studies relying on inductive designs are unable to study. When conducting spatial analysis, choosing the appropriate geographic unit of analysis (e.g., states, counties, census tracts) should be driven by theoretical arguments and/or empirical evidence regarding the manner in which others experience the impact or influence of the social process of interests.

Second, as Doreian (1980) points out, there are an infinite number of ways in which distance and contiguity can be measured in the spatial weights matrix. However, in specifying spatial dependence in models of crime and violence, the rule has been to follow Tobler's First Law of Geography (Tobler 1970, p. 236), which simply states, "... everything is related to everything else, but near things are more related than distant things." Furthermore, researchers often presume that spatial dependence follows a pattern of "spatial homogeneity," which Strang and Tuma (1993, p. 615) define as the assumption that all adjacent areas within "... the population have the same chance of affecting and being affected by each other." The result of following these dictums is the identification of a spatial weights matrix that is predicated solely upon geographic contiguity. Furthermore, when "row-standardized," the matrix imposes that each contiguous node impacts every other node to which the focal unit is linked and impacts them equally. The possibility of asymmetric relationships among neighbors is discounted, and the possibility that the events in non-neighboring areas can directly and strongly influence local levels of violence is ignored.

Finally, using a single matrix to capture processes of exposure and diffusion precludes the possibility of empirically differentiating between the two processes. The regression coefficient on the measure of spatial dependence provides an estimate of the overall impact that neighboring levels of violence have on local levels of violence. It does not, however, permit one to assess the relative impact of violence in neighboring areas vis-à-vis exposure or diffusion. Morenoff et al. (2001) make this point explicit by noting that their results achieved in the spatial analysis of homicide in Chicago were generally supportive of the exposure hypothesis, but that they are "... unable to pinpoint the relative contributions of exposure and diffusion... " (p. 552).

Failure to carefully account for the socio-spatial dimensions of the underlying social process in the modeling of the weights matrix leaves the interpretation of the spatial results open to criticism. The harshest criticism is that the spatial term is simply a "catch all" for any number of unobserved, residual processes. As Manski (1994, pp. 127–136) points out in his discussion of the "reflection problem," these unobserved processes may be the result of *endogenous processes* where the behavior being captured (violence) is simply the prevalence of violence within a particular reference group. This would be consistent with a process wherein similar others were grouped geographically and reacting to either exposure to violence or a set of subcultural norms that are consistent throughout the group. Alternatively, the spatial effect could be capturing a *contextual process* in which one's predilection to commit violence varies according to the characteristics of a particular reference group. Gang violence or other types of retaliatory violence in which the actors are influenced by the actions of others (the "reference group") is an example of a contextual process.

Demonstrating empirically the existence of a "spatial effect" often provides little guidance on which particular type of process is at work. This is especially true within the neighborhood effects literature because the precise mechanism by which place matters often remains unobserved or unmeasured in one's data (Manski 1994; Sampson et al. 2002).

Bringing the Deductive Approach to Spatial Models of Crime

The previous discussion makes clear that the correlation of events across nearby geographic units is not *sufficient* to establish that a process of spatial dependence exists. It is also the case that the presence of spatial autocorrelation based upon a traditional binary contiguity or inverse distance matrix is not a *necessary* condition to establish that social influence across space exists. In this section, we discuss how existing efforts to model spatial processes have moved beyond simple spatial adjacency. We explain how this can be applied to criminology by presenting a model of the influence of drug markets on patterns of violence. Our central empirical example models gun violence as a function of the location of rival street gangs.

There are several examples of innovative efforts outside of criminology that recognize that the processes by which actors in a focal area are influenced by the behaviors and actions of others are not neatly bounded by, or limited to, spatially adjacent or nearby areas. Gould (1991) finds that overall levels of resistance during the Paris Commune of 1871 were not influenced by levels of resistance in neighboring areas. Instead, resistance levels were greatest among those districts (*arrondissements*) that shared enlistments. The sharing of resources (resistance fighters) increased solidarity, which translated into greater overall effectiveness in the local insurgency's effort. More recently, Greenbaum (2002) explored the spatial distribution of wages among teachers in Pennsylvania and found that teachers' wages were more alike when contiguity among school districts was based upon the socio-economic similarity among districts. That is, wages in non-adjacent affluent school districts exhibited similar wages when compared to nearby non-affluent school districts. In addition, Babcock et al. (2005) modeled social comparisons among the same Pennsylvania school districts based upon referents identified in surveys. That is, during salary negotiations, school boards typically refer to a different set of neighbors than do the teacher unions, and the choice of reference districts affects the outcomes of the negotiations. State level budgets and fiscal policy are also known to be related to the expenditures and policies of "neighboring" states (Case et al. 1993). Not only are expenditures similar among spatially adjacent states, but they are also similar among states that are identified as "neighbors" because they share similarity in terms of median income and racial composition.

Within criminology, researchers are also beginning to take seriously the modeling of specific social processes, identified *a priori* to the specification of the W matrix, thought to influence the spatial distribution of violence. As noted above, recent work by Mears and Bhati (2006) examines the spatial distribution of homicide in Chicago by taking the novel approach of modeling exposure to violence by considering the impact of resource deprivation among both spatial neighbors as well as neighbors defined by social similarity that is unbounded by space. Their overall conclusion is that the impact of resource deprivation among socially similar neighborhoods is greatest when they are also spatially proximate. Interestingly, when homicides were disaggregated by type, neither spatial nor social adjacency was associated with levels of gang homicide. This finding is inconsistent with the *de facto* explanations provided in the spatial models of violence literature that often implicates the nature of gang violence as an explanatory factor in the clustering of events.

Modeling the Spatial Dynamics of Exposure

Of the ways in which events in one place can influence happenings in another, employing spatial weights matrix based upon simple geographic contiguity or inverse distance best approximates social process of exposure. There is ample evidence from the routine activities and environmental criminology literatures to suggest that living in close proximity to the types of neighborhoods that produce offenders will increase the ambient crime risk in an area.

The challenge to modeling this type of exposure spatially lies in how one chooses to implement "close proximity" in the W matrix. Fortunately there is a rich literature to guide this process as environmental criminologists have long concentrated on the well-traveled routes of *offenders* as the key to identifying why crimes happen where they do (Brantingham and Brantingham 1981). In fact, it has been demonstrated that the identification of abnormal spatial patterns can help uncover criminal activity (Kim 2007). Examining the journey to crime literature, one generally finds that offenders involved in homicide and assaults travel shorter distances than do offenders involved in other types of crimes (Boggs 1965; Rand 1986; Hesseling 1992). This suggests that the potential pool of victims of violence often resides close, but not necessarily in, the offender's own neighborhood. Short of constructing the W matrix by explicitly mapping the source and destination of all offenders, the empirical research offers at least some support for the adjacency-based approach to specifying W.

Two recent studies explored the influence of exposure to offenders on the spatial distribution of homicide in Chicago. Griffiths and Chavez (2004) combine Exploratory Spatial Data Analysis (ESDA) and Trajectory Analysis (Nagin 1999) and find a pattern that they identify with what they call a “defensive diffusion” effect (Griffiths and Chavez 2004, p. 967). They find that the census tracts that experienced increased gun homicide over time were located next to the tracts with the highest initial levels of violence. In other words, individuals were increasing their gun carrying, and ultimately usage, due to being exposed to violence in neighboring areas. Secondly, they point out that this spatio-temporal pattern is also consistent with offenders in the neighboring high rate tracks coming into the initially less violent tract and victimizing local residents.

By relying on a contiguity matrix, the two Chicago homicide studies assume that exposure is geographically bounded among first order neighbors. Again, this seems like a reasonable assumption. However, one could imagine instances where physical barriers such as major roads, open green spaces, or waterways inhibit such processes. For instance, drawing from environmental criminology, one could construct a travel network that measures the degree in which “neighbors” are truly accessible. Rather than using a binary contiguity or inverse distance matrix, one could then construct a weights matrix based upon the ease by which one can commute from one area to all other areas. Whether considering such impediments would alter the authors’ conclusions remains an empirical question.

Modeling the Spatial Dynamics of Diffusion

Much of the spatial analysis of violence literature uses data including the homicide peak of the early 1990s, a phenomenon known to be driven by the deadly combination of youth and guns. For many cities, the period also coincides with the arrivals of crack cocaine markets as well as violent urban streets gangs. It is little wonder, then, that drug markets and gangs emerged as the two primary explanations responsible for the spatial clustering and diffusion of violence. Furthermore, as we noted above, both involve features that are inherently attractive to notion of spatial diffusion; they both have very clear geographic dimensions and (presumably) involve retaliatory violence.

The location of drug markets is not random. There is now a rich literature demonstrating that, no different from any legitimate retail business, drug markets form in environment and settings that best serve participants. Dealers must make sure that their market is accessible and known to their customers and at the same time maximize their own personal safety by making sure that they can minimize law enforcement surveillance and escape from enforcement efforts (Caulkins et al. 1993; Eck 1995; Rengert 1996). Specifically, proximity to a freeway (Rengert 1996; Caulkins et al. 1993), central business district and transit stops (Robertson and Rengert 2006), and pay phones (Eck 1995) all make particular spaces good places to set up illicit drug markets.

Because drug markets do behave like other markets and have carefully chosen locations, drug markets eschew relocation. Though enforcement efforts might temporarily suspend operations within a given location, once the efforts subside, the market typically returns to its primary niche. When the geographically targeted enforcement efforts are successful, Weisburd and Green (1995) found that crime is not displaced into surrounding areas. In fact, they find that it is the crime reduction benefits of the enforcement that diffuses.

How might the impact of drug markets on local levels and patterns of violence be modeled? Perhaps it is best to consider drug markets as a special case of exposure where the drug market serves as a special class of a criminogenic factor. This would be in line with the suggestion of Blumstein's hypothesis regarding how crack markets lead to the diffusion, and ultimate use, of guns among urban youth. Given that one cannot report the theft of one's drugs or drug money to the police, Blumstein argues that drug dealers armed themselves to protect against robbery. As more youth became involved in the crack market, more youth began carrying guns. Soon, this "arms race" expanded to youth who were not active in the market, but rather "exposed" to the participants either through residential contacts or schoolyard interactions (Blumstein 1995; Blumstein and Cork 1996).

In this light, one could model the impact of the market on all those who are exposed to it, directly or indirectly. Many drug market participants reside outside of the immediate area (see Mikelbank and Sabol 2005; Tita and Griffiths 2005). Therefore, one might choose to link together the drug market with those neighborhoods from which both buyers and sellers are drawn. This would result in a spatial weights matrix made up of a series of discontinuous "islands" with the market linking neighborhoods similar to how an axel links the spokes in a wheel.

Urban street gangs are implicated even more frequently than drug markets as responsible for the patterns spatial dependence exhibited by violent crimes. Individual level studies consistently demonstrate that gang membership greatly increases violence and gun carrying (Battin et al. 1998; Thornberry et al. 2003; Gordon et al. 2004). Given the territorial and retaliatory natures of urban youth gang violence (Rosenfeld et al. 1999), it is natural to expect that gang-related violence would follow predictable spatial and temporal patterns. Because set space is a well-defined area in which gang members spend most of their time, one might expect set space to serve as a sort of lightning rod for inter-gang violence.

Whether the impact of gangs on patterns of gun violence is limited to only geographically adjacent areas is an empirical question that has gone unaddressed. We argue that the geography of gangs and their social networks suggest a set of structural properties that researchers have not adequately exploited in terms of understanding the spatial structure of gang violence. By combining gang turf maps with social network diagrams, it becomes possible to determine whether rival gangs are located in spatially adjacent areas, and thus the impact of gangs on spatial patterns of crime would be adequately captured in a simple contiguity matrix. If the socio-spatial dynamics of gang enmity are more complex – meaning that they span both simple contiguity and serve as links among non-local areas – then the spatial dependence matrix should be specified such that it is able to capture these complexities.

We do not suggest that exposure and diffusion represent an either/or proposition with respect to the manner in which gangs can influence gun violence. The spatial distribution of violence involving gang members may be explained by both exposure as well as diffusion. Given that gang members use guns more often than do non-gang members, a community that is exposed to gang members is likely to exhibit higher levels of gun violence. Those gang members may, or may not, live in spatially adjacent areas. Similarly, diffusion driven by the social interactions among gangs involved in ongoing rivalries may also explain the observed spatial patterning of gun violence, especially if the violence is primarily gang motivated and retaliatory in nature. The extent to which the interaction patterns of gang rivalries span simple contiguity to encompass non-local areas should inform the specification of one's spatial weights matrix.

Empirical Example: Gun Violence in Pittsburgh, PA

In this section, we demonstrate a deductive approach to modeling the impact of gangs on local patterns and levels of gun violence. The main goal of this empirical exercise is to show the validity of our approach and methodology rather than to directly answer broader theoretic or policy questions. Drawing from existing theories and prior empirical evidence from a similar study conducted on gang homicide in Los Angeles (Tita 2006), two spatial models are specified in addition to a model that ignores the role of space. The first spatial model follows the conventional approach and limits the influence of violence by restricting the impact among only spatially adjacent areas. The second spatial model considers the socio-spatial dimensions of gangs. Combining spatial data on gang locations with social network data on gang rivalries, we demonstrate how neighborhoods can be conceptualized as nodes in a larger spatial network, where links between nodes are dependent upon a specific social process such as gang rivalries. The central question, then, is whether additional insights can be gained by moving beyond spatial adjacency to consider explicitly the socio-spatial dimensions of gangs and their rivalries. If gang rivalries extend beyond geographic neighbors, the network-based matrix should better explain the observed spatial distribution of crimes in the study area.

This work addresses each of the three issues outlined earlier. First, two specific social processes are offered as the mechanisms driving how events in one location influence events in other places. Second, each of the two weights matrices reflects a specific social process. Third, because an explicit social process is being measured, we model the spatial process as spatial dependence and test that assumption.

Research Design and Measurement

The empirical analysis is conducted in a subset of neighborhoods in Pittsburgh, PA. The gangs that emerged in Pittsburgh are "traditional gangs" (Klein 1995) and have a strong attachment to turf (Tita et al., 2005). Tita and Ridgeway (2007) have demonstrated that the location of gang "set space," the places where gangs hang-out and come together to as a social entity, is strongly associated with local levels of gun violence.

Measures of Gang Set Space

The mapping of set space in Pittsburgh was accomplished through the participation of gang members as well as non-gang youth who resided in gang neighborhoods.[5] Set space represents small sections of the larger neighborhood from which the informants lived. Though these areas are smaller than the geographic units (census block groups) included in our analysis, block groups offer the smallest geographic unit for which the types of ecological measures important in the spatial analysis of crime are available. Analyses such as this are necessarily limited by the level at which data are aggregated (Oberwittler and Wikström, 2009), whereas individual-level network studies have the advantage that the unit of analysis and the attribute data exhibit a one-to-one correspondence.

For this application, we limit our examination to the portion of Pittsburgh bounded on the north/northwest by the Allegheny River and on the south/southwest by the Monongahela River. This simplifies the exercise by converting significant physical barriers into boundaries. Furthermore, Pittsburgh's gangs are concentrated in this region. Though the area includes just fewer than half of all block groups (244 of 497) in the city, it includes nearly two-thirds of all block groups containing set space (36 of 57). The study region and the location of gangs are shown in Fig. 7.1.

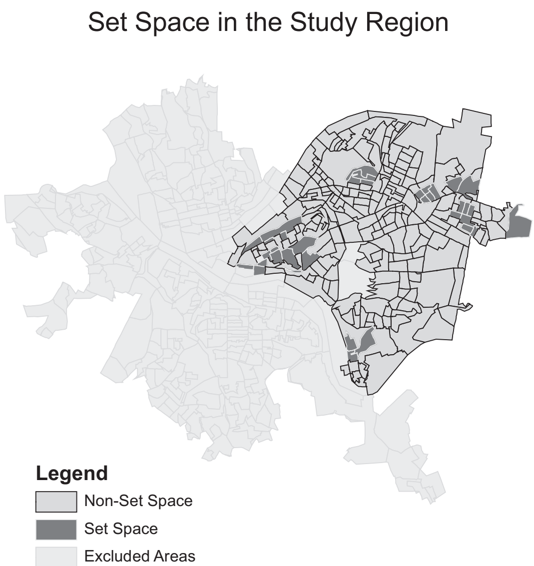

Fig. 7.1 Set space in the study region

[5] See Tita et al. (2005) for more detail on the methods used to map and validate the location of set space.

Measurement of Gang Rivalries

Gang rivalries were defined through interviews with the same set of informants who participated in the mapping project. Each participant was asked to identify those gangs that he considered to be their enemies. Though the mean number of rivals is 7.8, the gangs display a wide range in the number rivalries. The Formosa Way Crips and the Panke Way Crips have 17 and 13 rivals, respectively, though the Ehler Street Bloods, MPB, and BCK each have only three rivals.

Measures of Gang Violence

We use 911 calls-for-service to measure crime and limit the analysis to shots fired for the years 1992–1993. This is the period in which gangs formed and became embroiled in lasting rivalries, resulting in the highest levels of violence (Tita and Ridgeway 2007), especially gang-involved violence (Cohen and Tita 1999). The total number of shots fired incidents included in the study is 5762, or an average of 23.6 shots fired incidents per census block group (n = 244) over the two-year period. The spatial distribution of shots fired activity in the study area is shown in Fig. 7.2.

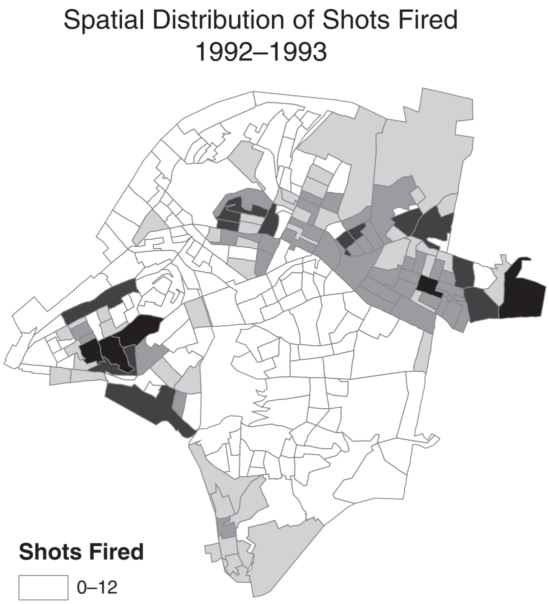

Fig. 7.2 Spatial distribution of shots fired 1992–1993

Calls for service depend on the willingness of local residents to report various criminal activities rather than on the choice of the police to enforce particular laws in particular places. Klinger and Bridges (1997) found serious under-reporting bias when using 911 data as a measure of total crime. They attribute this bias to the fact that 23 percent of all crimes handled by patrol officers emanate from police-initiated actions and not from civilian 911 calls. This type of undercounting is not a problem in Pittsburgh because a unique identifier is issued for each event regardless of whether it was citizen or police initiated. Duplicate calls have also been scrubbed from the data. In addition to crime type, the data contain information on the location and date of the incident. These data do not include information on the gang affiliation of the offenders or victims. However, because the focus of our study is on modeling the spatial patterns of gun violence, knowing the gang involvement of the individual participants is not crucial.

Ecological Measures

As displayed in Table 7.1, we included pertinent variables that have been shown to be related to gangs and gun violence in Pittsburgh (Tita et al. 2005; Tita and Ridgeway 2007). These include social control, social disorganization, underclass, and economic measures at the block group level. We also adjust for the percentage of the neighborhood residents who are Black and a control for the land area of the census block group measure of area. Definitions and descriptive statistics for the independent variables, along with the dependent variable, are presented in Table 7.1.

Measurement of the Weights Matrix

The geographically based spatial weights matrix (W_{g}) is based on first-order contiguity and was constructed using GeoDa 1.9 software (Anselin 2004). Rook's case contiguity was chosen, meaning that two census block groups are considered to be neighbors if they shared a common border.

The second weights matrix employed in this research is derived from the ties within the enmity network and the spatial location of the gangs' activity spaces (i.e., turf or "set space"). This matrix, W_{n}, was constructed by first creating a location-by-gang matrix, W_l, with dimensions of $m \times n$ (244 block groups $\times$ 27 gangs). This matrix was then multiplied by the $n \times n$ (27×27) enmity network, E, followed by the transpose of the location-by-gang matrix (27×244): $W_l E W_l$'. The resulting two-mode, $m \times m$ (244×244) matrix, W_n, identifies census block groups that contain "enemies" of one another. That is, a non-zero value of an element of W_{n}, $w_{i,j}$, indicates that the pair of block groups is linked because they both contain the turf of rival gangs. For those block groups that do not contain gang set space, we retained the spatial contiguity. As discussed earlier, both W_g and W_n are row-standardized so that neighbors have equal influence.

Table 7.1 Descriptive statistics

Variable	Definition	Mean[a]	Min	Max
Shots Fired (1992–1993)	Unique 911 calls regarding shots fired	23.615 (38.396)	0	276
1990 Census Measures				
Adult:Youth	Ratio of adults (ages 25–64) to youth (ages < 12)	4.66 (4.019)	0	30
Area (ln(1000s ft^2))	Natural log of block group's area in 1,000s of sq. feet	7.389 (0.817)	5	10
MedRent ($)	Median monthly rent for housing units ($)	379.525 (120.196)	116	825
%Black	% African Americans in population	39.926 (39.902)	0	100
%Renters	% Rental among housing units	44.852 (22.079)	0	100
NewBlack	= 1 if substantial growth of African Americans since 1960, = 0 otherwise	0.275 (0.447)	0	1
%Vacant	% Vacant housing units	10.656 (6.921)	0	48
Underclass	Index created based upon four measures of underclass[b]	34.369 (49.467)	0	315
NewRes	% Residents who did not live in same unit 5 years ago	42.447 (17.654)	7	100
%CrimeAge (14–24 yr olds)	% Population ages 12 to 24	16.881 (9.462)	0	86
%Over 64 (65 + yr olds)	% Population ages over 64	21.803 (10.390)	0	75
Boarded	= 1 if any houses in the block group are boarded up, = 0 otherwise	0.385 (0.488)	0	1
PerCapInc (per 1000)	Per capita income ($000s)	13.459 (8.946)	2.72	54.739
%BelowPov	% Population below poverty	23.504 (18.085)	0	83
%Unemp	% Unemployed among labor force participants	11.639 (11.008)	0	60
Pov>40%	= 1 if at least 40% population < poverty; = 0 otherwise	0.189 (0.392)	0	1
PopDen	People per 10,000 square feet	0.389 (0.505)	0	2

Notes: There are 244 observations.
[a] Standard deviations are in parentheses.
[b] % Population ages 18 to 25 with no high school degree
% Households receiving public assistance
% Households headed by females
% Males over age 15 not working at least 27 weeks in labor force

Models of Gun Violence

Standard OLS regression is inappropriate for estimating spatial lag models because *Wy* is endogenous. Maximum Likelihood Estimation (MLE) and two-stage least squares are both suitable alternatives (Anselin 1988; Land and Deane 1992), and we use MLE regressions to estimate the spatial lag model.

Results

Before reporting the results of the multivariate spatial analysis, it is customary to determine whether the spatial distribution of crime is random or exhibits a particular spatial pattern (i.e., it is spatially autocorrelated). The most common statistic used to determine the overall pattern of spatial autocorrelation is Moran's I, which is similar to a Pearson correlation coefficient.[6]

The test statistic, I, is bounded by 1.0 (perfect positive autocorrelation meaning the spatial clustering of like values) and -1.0 (perfect negative autocorrelation meaning dissimilar values cluster spatially), and statistical significance is based upon the standard normal distribution.

Using the contiguity spatial weights matrix, W_{g}, the Moran's I for the shots fired across all block groups is 0.325 (Z-value $=$ 8.562 and P-value $=$ 0.000). Repeating the analysis but using the network derived weights matrix, W_{n}, Moran's I is 0.442 (Z-value $=$ 12.046 and P-value $=$ 0.000). Based on both weights matrices, it is clear that the number of shots fired is not random across space. Though the test statistic is larger when the network-based W is used, it is incorrect to evaluate the two approaches based upon the magnitude of Moran's I. Instead, one needs to examine the significance level. Because the Z-value is greater for W_{n}, it would be correct to say that though the distribution of crime is both spatially and "socially" autocorrelated, the network-based measure better captures the type of dependence (social) than does the purely spatial measure of dependence.

The results of the regressions are presented in Table 7.2. Initially, the model was estimated with OLS with the constraint $\rho = 0$ imposed. The results of this estimation are reported in the first column of results in Table 7.2. The larger the physical size of the census block group, the more densely populated the block group, the block groups with the greatest growth in black residents since 1960, the higher the percentage of black residents, the higher the percentage of renters, the greater percentage of residents considered "underclass," and block groups with poverty rates greater than 40 percent based upon the 1990 census were are statistically significantly more likely to have more shots fired in the years 1992 and 1993. These results are consistent with other findings in the literature that show areas with higher levels of resource deprivation suffer higher levels of violent crime (Krivo and Peterson 1996; Morenoff et al. 2001; Mears and Bhati 2006).

[6] $I = \sum_i \sum_j w_{ij}(x_i - \mu)(x_j - \mu) / \sum_i (x_i - \mu)^2$

Table 7.2 Regression results

Coefficient	OLS	Geography *W*	Network *W*
Spatial lag	–	0.109	0.217**
		(0.090)	(0.086)
Adult:Youth	−0.278	−0.303	−0.266
	(0.540)	(0.518)	(0.510)
Area (ln(1000s ft^2))	11.385***	11.257***	10.907***
	(2.699)	(2.588)	(2.552)
MedRent ($)	−0.033	−0.032	−0.029
	(0.021)	(0.020)	(0.019)
%Black	0.155*	0.119	0.087
	(0.081)	(0.082)	(0.079)
%Renters	0.262*	0.282**	0.313**
	(0.144)	(0.139)	(0.137)
NewBlack	8.379*	7.983*	7.129
	(4.880)	(4.680)	(4.618)
%Vacant	−0.133	−0.157	−0.192
	(0.340)	(0.328)	(0.324)
Underclass	0.209***	0.202***	0.184***
	(0.067)	(0.064)	(0.063)
NewRes	−0.256	−0.269	−0.296*
	(0.188)	(0.180)	(0.177)
%CrimeAge (14–24 yr olds)	0.178	0.187	0.128
	(0.241)	(0.231)	(0.229)
%Over64 (65+ yr olds)	−0.362	−0.348*	−0.361*
	(0.220)	(0.211)	(0.208)
Boarded (1 if boarded properties, else 0)	7.854	7.244	5.958
	(5.411)	(5.190)	(5.130)
PerCapInc (per 1000)	0.108	0.118	0.107
	(0.309)	(0.296)	(0.292)
%BelowPov	−0.148	−0.147	−0.139
	(0.271)	(0.261)	(0.257)
%Unemp	0.143	0.150	0.111
	(0.279)	(0.267)	(0.263)
Pov>40%	14.994*	13.736*	12.562
	(8.689)	(8.330)	(8.213)
PopDen (people/10,000ft^2)	10.052**	9.434**	9.083**
	(4.359)	(4.179)	(4.121)
Constant	−66.476***	−66.694***	−64.477***
	(25.210)	(24.205)	(23.830)
R^{2a}	0.456	0.460	0.475

Notes: The dependent variable is shots fired between 1992 and 1993. N = 244
[a] For the MLE regressions, pseudo R^2 are reported
* p-value<0.1
** p-value<0.05
*** p-value<0.01
Standard errors are in parentheses.

Lagrange multiplier, and where appropriate, robust Lagrange multiplier tests were used to test the hypothesis of a spatially lagged dependent variable (Anselin et al. 1996). Despite the fact that the Moran's I indicated significant spatial correlation among shots fired across neighboring block groups as defined by the contiguity spatial weights matrix, W_{g}, including the set of explanatory variables in the regression model appears to account for much of the correlation across space. Lagrange multiplier tests for both the spatially lagged dependent variable (LM $=$ 1.385 and P-value $=$ 0.239) and spatially autocorrelated error term (LM $=$ 0.024 and P-value $=$ 0.877) do not indicate any remaining spatial dependence. However, as we argued above, patterns of influence are likely not bound exclusively by spatial proximity. We repeated the same tests for the network derived weights matrix, W_{n}. Lagrange multiplier tests help confirm the need for a spatially lagged dependent variable (LM $=$ 7.404 and P-value $=$ 0.007) rather than a spatially autocorrelated error term (LM $=$ 1.421 and P-value $=$ 0.233). The spatial lag dependence is further confirmed with a Lagrange multiplier test that is robust to any spatial autocorrelation (LM $=$ 10.040 and P-value $=$ 0.002).

The results of the MLE estimation of the spatial lag model using the geographic contiguity and network derived spatial weights matrices to create the spatially lagged dependent variable are displayed in the final two columns of Table 7.2. Not surprisingly given the results of the LM test, very little changed by including a spatially lagged dependent variable based upon W_g. The coefficient on the spatially lagged shots fired (0.109) is not significant at the 10 percent level and none of the other coefficients or the R^2 changed by very much by estimating this spatial model. However, inclusion of the more theoretically-justifiable lagged dependent variable based upon social networks and geography, W_n, does yield a significant coefficient on the spatial lag (0.217, P-value $<$ 0.05). Thus, for approximately every five additional shooting incidents in neighboring tracts, all else equal, the focal tract is predicted to have one more shooting incident. Inclusion of the spatially lagged dependent variable leads to a slightly better fit ($\mathrm{R}^2 = 0.475$). This suggests that social relationships across space do indeed impact the observed distribution of, and that that such linkages matter in ways that extend well beyond simple spatial contiguity.

Inclusion of the network generated spatial lag leads to some subtle changes in the estimated impacts of a number of the variables from the initial OLS estimation. Comparing the coefficients across the spatial and non-spatial models, we find that including the spatial lag resulted in the shrinking of the land area coefficient (11.385 to 10.907), population density coefficient (10.052 to 9.083), and percent underclass coefficient (0.209 to 0.184). The coefficients on the high poverty indicator variable (14.994 to 12.562) and percentage black (0.155 to 0.087) also shrank and became insignificant at the 10 percent level. The coefficients on the percentage of renters (0.262 to 0.313) and new residents (−0.256 to −0.296) increased slightly in absolute terms and became significant at lower significance levels. In the OLS model, all of these factors were likely capturing some of the effect of spatial dependence, thus biasing the estimated coefficients. Though such bias is important in and of itself, the true cost of ignoring the correct specification of the weights matrix lies in the ability to interpret the true impact of gang location and gang rivalries on patterns of gun violence.

Conclusions

A growing number of studies in the social sciences have adopted spatial regression in the effort to model and understand neighborhood effects (see Sampson et al., 2002). These efforts have used spatially lagged variables as proxies for social phenomena thought to be responsible for the consistent finding that spatial clustering of events related to the health and welfare of individuals remains even after controlling for local, contextual effects such as race, ethnicity, and poverty. The vast majority of these studies, however, only consider the possibility that the various social processes posited as responsible for the clustering matter only among spatially adjacent neighbors. Furthermore, even when multiple social processes are considered, the conventional modeling approach is to specify a single spatial weights matrix, thereby making it impossible to parse the impact of one process from that of another. Within the realm of criminology, models that interpret the spatial coefficient as being either the result of exposure to violence or the direct influence of diffusionary processes (especially drug markets and gangs) have no way to quantify either's independent contribution. Furthermore, the possibility that either influence process may extend beyond non-contiguous spaces is ignored.

Though our findings verify that researchers have been correct in suggesting gang rivalries play an important role in determining the observed spatial distribution of violence, the impact of these rivalries extends well beyond simple contiguity. That is, gangs have rivals, and these rivalries play an important role in influencing levels of violence in other neighborhoods, but the geographic scope of these rivalries is not limited to adjacent neighbors. By carefully considering socio-spatial dimensions of gangs in terms of the areas where they hang out and the rivalry networks that link them, it is possible to create a weights matrix that explicitly captures the geographic dimensions of the patterns of social influence among the gangs. We find that the violence, as measured by shots fired in a central part of Pittsburgh, is more a function of a social process that spans geography in such a way that violence in non-local areas impacts levels of violence in a focal neighborhood.

Though the current research focuses solely on the impact of gangs on patterns of gun violence, the lesson learned is far reaching for all types of analysis employing spatial regression in the study of violence. Most importantly, the results underscore Leenders' concern with the lack of careful consideration of the underlying social processes of influence exhibited by researchers in their construction of the weights matrices. Just as others have demonstrated the utility of disaggregating homicide by motive and other defining features in terms of understanding the social processes that lead to the commission of such crimes (Wolfgang 1958; Parker and Smith 1979; William and Flewelling 1988; Gartner 1990), it is important to consider socio-spatial processes that are specific to the type of events beings studied. For instance, testing the relationship between gun violence and drug markets would require one to specify a weights matrix that captures the important geographical information pertaining to the market (its location) as well as the spatial dimensions of the actors (mobility of customers and sellers) involved within the market. Adapting Leenders' (2002, p.26) "change one's theory, change W" statement to the current context and one is reminded to "change one's *crime*, change W."

The current research is also instructive for those who wish to use simple contiguity to capture processes beyond gangs, specifically issues addressing "exposure." Contiguity is theoretically justified when exposure is meant to capture social influence processes wherein local offenders from high violence areas transgress into *neighboring areas* to commit their crime, or when they influence residents in the *neighboring area* to carry/use guns. However, as research has demonstrated (Groff and McEwen 2006; Tita and Griffiths 2005), the distance traveled by homicide offenders differs by type of homicide. Therefore, care must be taken to construct spatial weights matrices that capture the links among neighborhoods that generate offenders and the neighborhoods where these offenders influence violence.

When the concern is tilted more to issues of social influence among peers or the contagious nature of subcultures, the geographic nature of these peers in terms of where they interact is extremely important. This is especially true among youth. As Mears and Bhati (2006) argue, the socio-spatial dimensions of these interactions is likely less dependent upon the location of residential neighbors and more likely dependent upon the geographic scale of one's social activities. This may include interactions at school, sporting events, bars/clubs, or other "staging areas" (Anderson 1999) where young people come together and interact. In fact, modeling ties among neighborhoods based upon the feeder patterns of local junior and senior high schools might offer excellent insight into the observed spatial patterns of violence and crime. Furthermore, it has also been demonstrated that homicide and gun violence have exhibited patterns of diffusion that are more consistent with hierarchical diffusion (among ordered pairs) than contagion diffusion along simple contiguity (Cohen and Tita 1999; Tita and Cohen 2004). Gun violence spread across communities not on the basis of geographic proximity, but more so in terms of social similarity. That is, violence spread along racial lines. Therefore, in modeling the diffusion of subcultures of violence or gun use, it may be necessary to consider the racial/social proximity among neighborhoods and not simply their geographic proximity to one another.

This research supports the basic conclusions reached in the spatial analysis of violence literature. First, place clearly matters. That is, levels and patterns of violence within geographic units cannot be explained by examining the structural characteristics alone. Second, the social organization of gang violence – as driven by geographic territory and enduring rivalries – is an important factor in accounting for spatial dependence. However, the common assumption that simple contiguity captures the social process of retaliation appears to be an oversimplification of socio-spatial dimensions of gang rivalries. That is, in some instances gang rivalries extend well beyond contiguous neighbors while in other cases neighboring geographic units are not linked through gang rivalries at all. As spatial analysis is used as a tool to identify the social processes responsible for "neighborhood effects," it becomes increasingly important to insure that one's spatial weights matrix is constructed in a manner that is consistent with the social process of interest.

When selecting the unit of analysis, we applaud the more recent literature that has begun to further explore the role of space. However, as we have shown, it is easy to specify a model incorporating space that does not adequately represent the social processes that underlie the spatial dependence. It is important to keep in mind that spatial autocorrelation does not necessarily imply spatial dependence – in that case, the autocorrelation is more appropriately modeled with a spatial error term that treats the spatial correlation as a nuisance parameter. However, as we make clear, many processes do lead to events in one place affecting outcomes in another, and the researcher must take care to use a deductive approach that models the social process that leads to the spatial dependence. As we have argued, this process may involve dependence among spatial units that are not geographically proximate. Future research should take care to consider this possibility.

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