SPATIALIZING SOCIAL NETWORKS: MAKING SPACE FOR THEORY IN
SPATIAL ANALYSIS


BY

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# ABSTRACT

This study is a quantitative and spatial analysis of the gang-related violence in a section of Los Angeles. Using data about the spatial distribution of gang violence in three neighborhoods of Los Angeles, this research first adopts a deductive approach to the spatial analysis of gang violence by spatial regression models that considers the relative location of the gangs in space while simultaneously capturing their position within a social network of gang rivalries. Several models are constructed and compared and the model that seems to best fit the observed geography of violence is one in which both the territorial geography and the social geography of the gangs is utilized in the autocorrelation matrix. Building on the findings of the spatial regression modeling, the concept of social position and associated techniques of structural equivalence in social network analysis is then explored as a means to integrate these different spatialities. The technique of structural equivalence uses the two different spatialities of embeddedness to identify gangs that are similarly embedded in the territorial geography and positioned in the rivalry network which aids in understanding the overall context of gang violence. The importance of theory to guiding spatial regression modeling is demonstrated by these findings and the hybrid spatial/social network analysis demonstrated here has promise beyond this one study of gang crime as it operationalizes spatialities of embeddedness in a way that allows simultaneous systematic evaluation of the way in which social actors' position in network relationships and spatial settings provide constraints and possibilities upon their behavior.

*To Jennifer, Maxwell, and Kira.*

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# CHAPTER 1

# INTRODUCTION

The recognition of geography as a factor in the explanation of a multitude of social phenomena has been an increasingly notable component of quantitative social science (Goodchild et al. 2000). Research produced in a variety of disciplines now incorporates geographic or spatial elements into analysis that utilizes quantitative methodologies. An important reason for the adoption of spatial perspectives for quantitative social science has been a growing recognition of the importance of context to human action. As Flint (2002: 34) argues, spatial perspectives are now important in social science because "people with similar socioeconomic and cultural characteristics are likely to behave differently within unique contextual settings" and incorporating context into quantitative models of human behavior is the ongoing focus of the subfield of spatial analysis and spatial statistics within human geography.

The analysis of spatial phenomena in social science has been made possible in recent years by the ongoing development of statistical techniques that attempt to deal with some of the unique problems of spatial data, especially spatial dependence. Dependence, or the tendency of characteristics of a given location to correlate with those of nearby locations, is a foundational issue in quantitative geographical analysis (e.g., Anselin 1988; Cliff and Ord 1981; Cressie 1993; Griffith 1987; Haining 1990, 2003). These methods, commonly called spatial econometrics, were once of interest to a small set of spatial statisticians and quantitative geographers. However, spatial econometric models that deal with dependence are now increasingly of interest to large numbers of researchers from diverse disciplines investigating a wide range of issues (e.g., Ward and

Gleditsch 2008). Many social scientists now view spatial econometric regression models as an improvement on non-spatial techniques as a result of the growing recognition that dependencies in the spatial structure of research data may limit the inferences of quantitative investigations (Anselin et al. 2004).

Spatial econometric regression models demand a careful consideration of both the theoretical and empirical spatial structure of the data in question (e.g., Florax and Rey 1995). However, the advent of new spatial econometric software packages has lowered the traditional technical barriers to the use of these techniques while simultaneously making it easy for users to choose among a few predefined spatial structures.[1] New users may therefore be unfamiliar with the importance of the formal spatial structure to analytic outcomes and less likely to carefully consider their choice (see Leenders 2002). The small literature new users may draw upon to understand this issue remains quite technical in nature, even when proclaiming the opposite intent (e.g., Griffith 1996). Taken as a whole, this state of affairs is less than ideal and unlikely to encourage careful thinking about space. However, the need to formalize the empirical spatial structure of the data for modeling is also an opportunity to reflect on the theoretical interaction of the geography and social processes being studied. In this manner, spatial analyses of human behavior and outcomes is at the core of the emerging "spatially integrated social science" identified by Goodchild et al. (2000), and an opening for the investigation of how human behavior and space are mutually constituted.

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[1] Examples of spatial econometric software include The "GeoDa" software package (see Anselin et al. 2006 and https://www.geoda.uiuc.edu/) and the "spdep" package in the open source R environment (see Bivand 2002). GeoDa allows users to create spatial weight matrices from data created in a geographic information system (GIS) and spdep will read in matrices created in GeoDa.

In light of this state of affairs, this dissertation has a twin purpose. First, I attempt to build upon the current energy in spatial analytical modeling across social science to offer a unique contribution by demonstrating the importance of incorporating theory about the phenomenon of interest into spatial modeling efforts. Second, I offer a new methodological approach to incorporating theory into spatial modeling. The chapters that comprise this dissertation are drawn from a series of publications directly related to these twin goals using data on the production of a particular kind of violence in an urban context. This dissertation examines gang-related violence within a small area of the city of Los Angeles and each chapter focuses on a particular element or challenge involved in producing a theoretically informed spatial analysis using the same data and issue.

RESEARCH PROBLEM

As typically argued in many geographic literatures and, increasingly, in other social science literatures, spatial perspectives are important for both theoretical and practical reasons. Theoretically, spatial perspectives are of interest because of the "longstanding interest in the social production of space" in geography (Cox et al. 2008: 6). Following Lefebvre's (1991) understanding of space as both social process and social product, the spatial structures of a given phenomena are commonly investigated as underlying cause, constructed outcome, or both. For example, the perception of rivalries over territorial control between a set of gangs and the actual construction of bounded turf are simultaneously social and geographic phenomena. The competitions are inseparable from the geography and vice versa. Hence modeling a social process such as gang rivalry requires modeling the social construction of spaces (Flint 1998).

On the other hand, consideration of geography is a practical methodological matter. Data with a geographical component has important implications for statistical analyses; if processes that are affected by the underlying spatial structure in a study area are not accounted for, inferences will be inaccurate and estimates of the effects of independent variables may be biased (Anselin 1988). Perhaps the most important reason for the interest in quantitative spatial methods is the most straightforward: nearly all social science data is spatially organized and ignoring this structural element is increasingly seen as untenable (Ward and Gleditsch 2008). To accommodate these issues, statistical models have been developed that attempt to deal with issues of spatial dependence. Conventionally, this is done through either introducing an additional covariate (referred to as a 'spatial lag' variable which is a weighted average of values for the dependent variable in areas defined as 'neighbors') or by specifying a spatial stochastic process for the error term. These models are now seen as both viable and important for social science research (Ward and Gleditsch 2008).

These models have been discussed and exemplified in depth (see Anselin 2002 for an overview) but an essential element of these models remains largely ignored in the literature, despite the major theoretical and methodological implications. Both the lag and error models attempt to estimate regression parameters in the presence of presumably interdependent variables (Anselin 1988; Leenders 2002). This estimation process requires the analyst to define the form and limits of the interdependence and formalize the influence one location has on another. In practice, this is accomplished by identifying the connectivity between the units of the study area through a $n \times n$ matrix. The matrix is

usually described in the literature as a 'spatial weight' or 'spatial connectivity' matrix and referred to in the preceding lag and error models as "*W*".

This *W*, or matrix of locations, formalizes a priori assumptions about potential interactions between different locations, defining some locations as influential upon a given location and ruling others out. A simpler way of describing this is that *W* identifies, in some cases, who is a neighbor and who is not, or with whom an actor interacts. However, the construction of *W* is more than just an empirical choice about neighbors. It is a theoretical decision regarding the spatiality of the social processes being discussed and one that has implications for the statistical estimates generated.

As *W* is supposed to represent a formal model of connections between geographic locations, how one translates theories about influence and its mechanisms across space into a formal mathematical construct is an important step. Put another way, at its core, *W* is really a theoretical geography of interaction. However, as a practical matter, the spatial analytic geography literature focuses on modeling interaction through a distance-based logic that typically takes one of two forms: contiguity or distance (Cliff and Ord 1981; Griffith 1996). Both of these spatial themes have been mobilized for constructing *W*'s for various kinds of measures of spatial autocorrelation dating back to Cliff and Ord's seminal work (1981). Contiguity, or the physical connections between locations, is emphasized in issues that focus on areal spaces, especially ecological studies that use aggregated data. Distance between locations of interest remains an important concept to many kinds of geographic literatures. In the case of issues of society and space, the

geography of influence is typically imagined and implemented in the models as a kind of gradient that uniformly diminishes with increasing distance.[2]

The development and dissemination of spatial analytic software allows users to easily create *W*'s from spatially organized data using the classic spatial forms of areal contiguity or point-to-point distance. And while such software often guides researchers through the practical steps needed to create a theoretical geography of spatial interaction or influence, there is no drop-down menu to offer guidance as to how best to capture the geography, or spatiality, of the social processes being analyzed. For any given research topic, are immediately contiguous areal neighbors enough, or should more distant neighbors also be included? If distance matters, at what distance does influence begin to diminish? More to the point, why and in what way does distance "matter" in the operation of the social process under investigation? These questions remain the key challenges for a theoretically informed spatial analysis.

Somewhat surprisingly, discussions about the nature of *W* and how different specification choices may affect regression results have also been underemphasized in most spatial analytic literature: the relatively few examples to the contrary include Florax and Rey (1995) and Griffith (1996). Despite these noteworthy efforts, Leenders is correct in his assessment that "the effort devoted by researchers to the appropriate choice of *W* pales in comparison to the efforts devoted to the development of statistical and mathematical procedures" (2002: 44).[3] The net effect of this lack of attention is that

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[2] For classic examples of distance-based thinking in social science, see Boulding (1962) and Tobler (1970). Boulding's (1962) "Loss of strength gradient" argued that military power has a direct inverse relationship with distance and Tobler (1970) described the so-called 'first law' of geography when he stated that everything is related to everything else, but near things are more related than are far things.

[3] Like many others, Ward and Gleditsch (2008: 60) acknowledge that "small perturbations in the weight matrix will have salient consequences in the empirical results." As an example of an exception that proves

theoretical conceptions about the role space plays in producing empirical patterns in a given dataset are often afterthoughts. Hence, the vision of a "spatially integrated social science" (Goodchild et al. 2000) remains unfulfilled, because when space is included in the analysis of social processes it is often added in a default form without consideration of the geographic expression of the processes in question. This issue was the key motivation behind this research and underpins the efforts presented in the following chapters.

STUDY SITE AND DATA

The chapters that comprise this dissertation focus on violence involving urban street gangs in the Hollenbeck Community Policing Area in Los Angeles, CA. Located east of downtown Los Angeles, the Hollenbeck Policing Area has a population of roughly 200,000 people, is 15.2 square miles in size, and encompasses the communities of El Sereno, Lincoln Heights, and Boyle Heights (Los Angeles Police Department 2008). According to U.S. Census statistics, most of the population is Latino (84.5%) and nearly forty percent (39.4%) of the total population was born in Mexico. Thirty percent of the population lives below the poverty line and of the total population that is at least twenty-five years old, thirty five percent has less than a high school degree or equivalent (Tita et al. 2003).

According to Tita et al. (2003), homicide rates in Hollenbeck have been higher than both Los Angeles and U.S. national homicide rates since the early 1990s. Hollenbeck consistently ranks among the top three or four of the Los Angeles Police

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Leenders' rule, Ward and Gleditsch's (2008: 77–80) three paragraphs on the topic is perhaps the most comprehensive discussion of the implications of *W* for social scientists.

Department's (LAPD) 18 policing areas in violent crime. LAPD crime statistics for 2007 show that violence in Hollenbeck remains high as there were 799 violent crimes reported in the Hollenbeck area (Los Angeles Police Department 2008). Gangs and gang-related issues are central to violent crime in Hollenbeck: gangs were involved in nearly 75% of all homicides in Hollenbeck from 1995 to 1998 (Tita et al. 2003) and in a 2008 report by the Los Angeles County District Attorney, the Hollenbeck Policing Area was classified as an area of "Very Heavy Gang Activity," the highest category of the classification scheme used in the report (Cooley 2008: 45).

Tita et al. (2003) argues that the combination of physical barriers and social geography that define the Hollenbeck Community Policing Area serve to limit interactions with gangs from neighboring areas. For example, Hollenbeck is delimited in the west by the Los Angeles River and along the northwest by the Pasadena Freeway. The city of Vernon, CA, which lies to the immediate south of Hollenbeck, is an industrial area with a total population of only 91 at the 2000 census (see Figures 4.1 and 5.1 in Chapters 4 and 5, respectively). Thus, there no are spatially proximate gangs in either of these directions. To the southeast, Hollenbeck is bordered by an unincorporated area of Los Angeles County (East Los Angeles) and to the northeast by the city of South Pasadena. Both of these areas do have urban street gangs, yet none of these gangs routinely interact with the Hollenbeck gangs. Although no physical barrier serves to impede movement between Hollenbeck and either East Los Angeles or South Pasadena, the fact that each is served by different public school districts greatly shapes the across-place social interactions, including those of street gangs (Grannis 2009). The net effect of these features, both physical and social, is to create a landscape within which the rivalries

of the gangs within Hollenbeck are wholly contained (Tita et al. 2003). For these reasons, the Hollenbeck Community Policing Area comprises the spatial extent of this study as all the interactions under consideration are wholly contained within the neighborhoods that make up Hollenbeck.

The history of urban street gangs in east Los Angeles, including Hollenbeck, is a long one, with some gangs documented back to the late 1940s (Moore 1991). From 2000 to 2002, 29 active gangs were identified in the Hollenbeck area (Tita et al. 2003). Control over territory is a central theme for the gangs of Hollenbeck. The gangs in Hollenbeck are what Klein (1995) describes as 'traditional' in that they have a strong attachment to turf, or the territory under the direct control of a gang. Tita et al. (2003) makes a similar argument and characterizes the gang violence in Hollenbeck as expressly tied to the defense of turf and control over territory. The key point here, made by Sack (1986) and others (e.g., Paasi 2003), is that territory is not the static result of social processes but is instead what Newman calls an "imperative" and an "essential component of human behavior" (2006, 88-89). The attempts by the various gangs to control the spaces of Hollenbeck result in violence between the different street gangs themselves and are likely key to understanding the spatial patterning of gang violence in Hollenbeck.

The empirical chapters of this dissertation use data on the spatial distribution of gang-related violence in Hollenbeck, information about the relationships between the gangs themselves, the extent of their territorial claims, and demographic information about Hollenbeck aggregated by Census block group. From 2000-2002, Hollenbeck experienced 1,223 violent crimes by or against gang members. This kind of gang related violence over this time period include the legal classifications of aggravated assaults,

simple assaults, assault with a deadly weapon, attempted homicides, homicides, robberies, kidnappings, and firing a gun into an inhabited dwelling/vehicle. The data on gang-related violence and information about the gangs themselves (relationships and territorial extents) were originally collected by Tita et al. (2003) and used again for the empirical chapters of this dissertation.

ORGANIZATION

The material presented in this dissertation has been previously published as part of an ongoing collaboration built around the goal of producing a theoretically informed spatial analysis. Because each chapter is also from one of four stand alone publications, this dissertation is not organized in the conventional fashion, with separate chapters for literature reviews, theory, and empirics. However, the nature of the four publications that comprise the chapters of this dissertation mimics this traditional organization to some degree, providing literature review, theory, and empirical chapters. Chapter 2 presents an overview of the literature of the spatial analysis within the field of criminology and offers a detailed discussion of the spatial regression models commonly used to model influence and interaction. This chapter, originally published as a book chapter in the *Handbook of Quantitative Criminology* (Tita and Radil 2010b), is most like a traditional dissertation literature review and is included in that spirit. Similarly, Chapter 3 is drawn from a conceptual essay published in a special issue of the *Journal of Quantitative Criminology* (Tita and Radil 2010a) and is a discussion about a theoretical framework for understanding and modeling context by building on the place concept in geography that

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emphasizes connections between places. Therefore, Chapter 3 may also be seen as akin to a theory chapter in a traditional dissertation format.

Chapters 4 and 5 present the empirics of this research. Chapter 4, also published in the *Journal of Quantitative Criminology* (Tita and Radil 2011), examines alternative specifications of the spatial weights matrix and compares more common distance-based (adjacency-based) specifications with those that are more explicitly grounded in a theory of competition between the gangs. These alternative specifications are used in spatial regression models and the impact of the different specifications on model performance is evaluated. An important finding from this chapter is that a 'hybrid' spatial weights matrix can be constructed that captures both distance-based and social relationship-based interactions. This finding leads directly to the research presented in the next chapter.

Chapter 5, the last of the empirical chapters and published in the *Annals of the Association of American Geographers* (Radil et al. 2010), blends concepts and techniques from social network analysis with conventional spatial analysis to theorize the socio-spatial processes involved in the 'hybrid' weights matrix from the previous chapter and to perform an analysis of the spatial patterning of violence using a social network analysis methodology. This research finds evidence for the production of differential spaces of violence in Hollenbeck, which I interpret as partial evidence of the social production of space, which is both made by and a mediator of the agencies of the gangs themselves.

I conclude the dissertation with a discussion that synthesizes the information presented in each chapter by returning to the theme of the social construction of space and the pressing need to incorporate theory into spatial modeling. It is my hope that the

work I have done to this end demonstrates not just the need for such analyses in social

science, but also the possibilities that such work can offer.

**CHAPTER 2**

**SPATIAL REGRESSION MODELS IN CRIMINOLOGY**

This chapter presents an overview of the literature of the spatial analysis within the field of criminology and offers a detailed discussion of the spatial regression models commonly used to model influence and interaction. This material was originally published as a book chapter in the *Handbook of Quantitative Criminology* (Tita and Radil 2010b) and is much like a traditional dissertation literature review. As such, it is offered with that purpose in mind and is presented here largely unaltered from Tita and Radil (2010b) aside from minor formatting changes.

INTRODUCTION

A decade ago, Jacqueline Cohen and George Tita served as guest editors for a special volume of the *Journal of Quantitative Criminology* (Vol 15, #4, 1999) that was dedicated to the study of the diffusion of homicide. In their Editor's Introduction (Cohen and Tita 1999a), they concluded that the results presented in special volume,[4] along with recent work by Morenoff and Sampson (1997), clearly demonstrated that the observed patterns of violence were consistent with patterns one might expect if violence does in fact diffuse over space. That is, levels of violence are not randomly distributed; instead similar rates of violence cluster together in space (i.e., violence exhibits positive spatial autocorrelation). Furthermore, a growing number of studies began to demonstrate that even after controlling for the ecological features known to be associated with high levels of crime (e.g., poverty, population density, male joblessness, female-headed households,

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[4] The contributors to this special issue included Cork; Mencken and Barnett; Messner, Anselin, Baller, Hawkins, Deane and Tolnay; Cohen and Tita; and Rosenfeld, Bray and Egley.

etc) the clustering of high values could not be explained away. These early spatial studies of diffusion helped to establish the existence of an unobserved "neighborhood effect" that seemed to be responsible for spatially concentrated high-crime areas.

Not to diminish the contribution of these studies in advancing our understanding of crime and violence, Cohen and Tita (1999a) ended their introduction by noting that there was much work to be done[5]. First, in order to understand diffusion, models needed to include a more complete accounting of temporal considerations. Though the spatial analysis of cross-sectional data is helpful in determining whether or not the initial conditions consistent with diffusion are being satisfied, without analyzing change over time one can not capture the movement of spatial patterns over time. Second, even during the homicide epidemic of the late 1980s and early 1990s, homicide remained a rare-event when compared to other types of crimes. In order to fully understand the mechanisms that drive the diffusion of violence, research needed to be conducted on non-lethal violence (as well as other types of crime.) According to the authors, however, the single most daunting challenge facing the researchers was not developing better methods or using better data in order to validate patterns of diffusion; the most important hurdle was to create models that would produce results that could be used to gain a better understanding of the "…mechanisms by which the recent homicide epidemic spread."  In other words, Cohen and Tita called upon to the research community to create models that would help to unlock the black box of "neighborhood effects" by explicitly modeling the processes that drive the spread of violence.

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[5] Cohen and Tita neglect to address the issue of employing the appropriate spatial scale in terms of the spatial unit of analysis. Hipp (2007) and Weisburd et al. (2008) offer excellent treatment of this important topic.

We hope to achieve several goals in this chapter. Though the term "spatial analysis" can be applied to a broad set of methodologies (e.g., hot spot analysis, journey to crime analysis, exploratory spatial analysis)[6] we wish to focus specifically on the application of spatial regression models to the ecological analysis of crime, which makes use of socio-economic data aggregated or grouped into geographic areas. To do so, however, requires an introductory discussion of the nature of spatial data and the associated exploratory analyses that are now common when using geographically aggregated data. Therefore, we begin with an overview of spatial data with an emphasis on the key concept of spatial autocorrelation and provide an overview of exploratory spatial analysis techniques that can assess the presence and level of spatial autocorrelation in spatial data. We then move on to a discussion of spatial regression models developed to address the presence of spatial effects in one's data. Next we highlight some of the key findings that have emerged from the use of spatial regression in criminology and evaluate whether or not they have helped in the identification of the particular social processes responsible for the clustering and diffusion of crime. Drawing upon our own work (Tita and Greenbaum 2009; Radil et al. 2010; Tita and Radil 2011b), we hone in on one of the most important, though often overlooked, components of any spatial regression model – the spatial weights matrix or "*W*." We believe that the mechanisms and processes that drive the diffusion of crime can best be understood by "spatializing" the manner in which information and influence flows across social networks. Therefore, we examine some of the innovative ways that researchers have used to specify "*W*" in criminology as well as other areas of study. Keeping Cohen and Tita's

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[6] For an introductory treatment of these methods and the manner in which they have been used in criminology and criminal justice, see Anselin, Griffiths and Tita (2008.)

(1999) argument about unlocking the black box of "neighborhood effects" in mind, we conclude by emphasizing the importance of theoretically- and empirically-grounded specifications of *W* to this goal.

THE NATURE OF SPATIAL DATA AND SPATIAL DATA ANALYSIS

Criminology, like most social sciences, is an observational science as opposed to an experimental science. This is to say that researchers are not able to experiment with or replicate observed outcomes, which take place at specific locations at specific times. When the structure of the places and spaces in which outcomes occur is thought to affect the processes theorized to give rise to the observed outcomes (such as theorized relationships between crime and place – see Morenoff et al. 2001 or Sampson et al. 2002 for recent examples), the location of each outcome is important information for researchers. Spatial data then are those with information about the location of each observation in geographic space.

A fundamental property of spatial data is the overall tendency for observations that are close in geographic space to be more alike then are those that are further apart. In geography this tendency is referred to in 'Tobler's First Law of Geography' which states that "everything is related to everything else but near things are more related than distant things" (Tobler 1970: 236). Although more of a general truism than a universal law, Tobler's 'law' rightly points out that the clustering of like objects, people, and places on the surface of the earth is the norm and such organizational patterns are of intrinsic interest to many social scientists (O'Loughlin 2003; Haining 2003). This property is called *spatial dependence* and has important implications for researchers. First, an

observation at any given location can provide information about nearby locations and one can therefore make informed estimates about the level of attributes in nearby locations (e.g., spatial interpolation). Second, the tendency of data to vary together across space creates problems for classical inferential statistical models and can undermine the validity of inferences drawn from such models (Anselin 1988).

Another fundamental property of spatial data is the tendency for relationships between variables to vary from place to place or across space. This tendency, known as *spatial heterogeneity*, is often due to due to location-specific effects (Anselin 1988; Fotheringham 1997). Spatial heterogeneity has the important consequence of meaning that a single global relationship for an overall study region may not adequately reflect outcomes in any given location of the study region (Anselin 1988; Fotheringham 1997). Further, variations in local relationships can lead to inconsistent estimates of the effect of variables at global levels if the relationship between the dependent variable of interest and the independent variables is characterized by a non-linear function (Fotheringham et al. 2002).[7]

Both of these properties of spatial data have been at the heart of spatial data analysis, the development of quantitative analytic techniques that accommodate the

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[7] We also wish to draw attention to another group of properties directly or indirectly related to how spatial data is represented, organized, and measured by researchers. While not an exhaustive list, border effects, the so-called 'modifiable areal unit problem,' and the challenges of ecological fallacy are three issues commonly encountered by researchers using aggregated spatial data (see Haining 2009). Border effects refer to the fact that the often-arbitrary boundaries of study regions may exclude information that affects outcomes within the study region (see Griffith 1983). The modifiable areal unit problem (MAUP) refers to the fact that the results of statistical analysis, such as correlation and regression, can be sensitive to the geographic zoning system used to group data by area (see Gehlke and Behl 1934 or Robinson 1950 for classic examples of MAUP, or Openshaw 1996 for a more contemporary review). Ecological fallacy, or the difficulty in inferring individual behavior from aggregate data, is ever present in many social sciences attempting to predict individual behavior from an analysis of geographically aggregated data (see King 1997; O'Loughlin 2003) While well-established in geography, these issues tend to resurface in other disciplines as spatial analysis becomes more prevalent (for an example, see Hipp 2007). For a review of the treatment of some of these issues in the spatial analysis of crime, see Weisburd et al. (2008).

nature of spatial data for both descriptive and inferential statistical analysis and modeling (Anselin 1988; Haining 2003; Goodchild 2004). Anselin (1998) has referred to the collection of different methods and techniques for structuring, visualizing, and assessing the presence of degree of spatial dependence and heterogeneity as exploratory spatial data analysis, or ESDA. For Anselin (1998), the key steps of ESDA involve describing and visualizing the spatial distributions of variables of interest; the identification of atypical locations (so-called 'spatial outliers'); uncovering patterns of spatial association (clusters); and assessing any change in the associations between variables across space. While a comprehensive review of ESDA is beyond the scope of this chapter (see Anselin 1998, 1999), we wish to draw attention to the concept of spatial autocorrelation which is commonly present in data aggregated to geographic areal units and is therefore of relevance to criminologists that commonly use such data.

Spatial dependence in spatial data can result in the *spatial autocorrelation* of regression residuals. Spatial autocorrelation occurs when the values of variables sampled at nearby locations are not independent from each other. Spatial autocorrelation may be either *positive* or *negative*. Positive spatial autocorrelation occurs when similar values appear together in space, while negative spatial autocorrelation occurs when dissimilar values appear together. When mapped as part of an ESDA, positively spatially autocorrelated data will appear to cluster together, while a negatively spatially autocorrelated data will result in a pattern in which geographic units of similar values scatter throughout the map (see Figure 2.1).

The presence of spatial autocorrelation may lead to biased and inconsistent regression model parameter estimates and increase the risk of a type I error (falsely

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rejecting the null hypothesis). Accordingly, a critical step in model specification when using spatial data is to assess the presence of spatial autocorrelation. And while different methods have been developed to address issues of spatial heterogeneity, such as identifying different spatial regimes (sub-regions) and modeling each separately (Anselin 1988), spatial dependence must still be addressed within distinct sub-regions once these have been identified.

A number of statistical methods have been developed to assess spatial autocorrelation in spatial data both globally and locally. As described in the seminal works in geography on spatial autocorrelation by Cliff and Ord (1973, 1981), the basic standard tests for spatial autocorrelation are the join count statistic, suited only for binary data, and more commonly, Moran's $I$ and Geary's $C$, both suited for continuous data (Cliff and Ord 1973, 1981). Moran's $I$ and Geary's $C$ are global measures of spatial autocorrelation in that they both summarize the total deviation from spatial randomness across a set of spatial data with a single statistic, although they do so in different ways. Moran's $I$ is a cross-product coefficient similar to a Pearson correlation coefficient and ranges from -1 to +1. Positive values for Moran's I indicate positive spatial autocorrelation and negative values suggest positive spatial autocorrelation. Geary's $C$ coefficient is based on squared deviations and values of less than one indicate positive spatial autocorrelation, while values larger than one suggest negative spatial autocorrelation. As a counterpart to the global statistics, there are also local statistics that assess spatial autocorrelation at a specific location. These include the Getis and Ord $Gi$ and $Gi*$ statistics (Getis and Ord 1992; Ord and Getis 1995) and the local Moran's $I$ (Anselin 1995).

SIMULTANEOUS AUTOREGRESIVE SPATIAL REGRESSION MODELS

While there are a variety of methods to address spatially autocorrelated data in regression models, we focus here on what are commonly referred to as simultaneous autoregressive (SAR) models, the standard workhorse in spatial regression in a variety of social science fields, particularly those that make use of spatially aggregated socio-economic data (Anselin 2006; Ward and Gleditsch 2008). Spatial regression models, including SAR models, have been in large part developed as a response to the recognition that ignoring spatial dependence when it is present creates serious problems. As Anselin (1988) and others have demonstrated, ignoring spatial dependence in spatial data can result in biased and inconsistent estimates for all the coefficients in the model, biased standard errors, or both. Consequently inferences derived from such models may be significantly flawed. While a thorough treatment of these models is beyond the aims of this chapter, we offer a brief summary of the main variants before moving on to offer some examples of how these models have been used in criminology.

SAR models can take three different basic forms (see Anselin 1988, 2002; Haining 2003). The first SAR model assumes that the autoregressive process occurs only in the dependent, or response, variable. This is called the 'spatial lag' model and it introduces an additional covariate to the standard terms for the independent, or predictor variables and the errors used in an ordinary least squares (OLS) regression (the additional variable is referred to as a 'spatial lag' variable which is a weighted average of values for the dependent variable in areas defined as 'neighbors'). Drawing on the form of the

familiar OLS regression model and following Anselin (1988), the spatial-lag model may be presented as

$$Y = \rho Wy + X\beta + \varepsilon,$$

where $Y$ is the dependent variable of interest, $\rho$ is the autoregression parameter, $W$ is the spatial weights matrix, $X$ is the independent variable, and $\varepsilon$ is the error term.

The second SAR model assumes that the autoregressive process occurs only in the error term. In this case, the usual OLS regression model is complemented by representing the spatial structure in the spatially dependent error term. The error model may be presented as

$$Y = X\beta + \varepsilon, \ \varepsilon = \lambda W\varepsilon + \mu,$$

where $\lambda$ is the autoregression parameter, and $\varepsilon$ is the error term composed of a spatially autocorrelated component ($W\varepsilon$) and a stochastic component ($\mu$) with the rest as in the spatial lag model. The third SAR model can contain both a spatial lag term for the response variable and a spatial error term, but is not commonly used. Other SAR model possibilities include lagging predictor variables instead or response variables. In this case, another term must also appear in the model for the autoregression parameters ($\gamma$) of the spatially lagged predictors ($WX$). This model takes the form

$$Y = X\beta + WX\lambda + \varepsilon.$$

Combining the response lag and predictor lag terms in a single model is also possible (sometimes referred to as a 'mixed' model).

As Anselin (1988) observes, spatial dependence has much to do with notions of relative location between units in potentially different kinds of space and, accordingly, SAR models share a number of common features with network autocorrelation models.

Substantively, spatial and network approaches have been used to explore similar questions pertaining to influence and contagion effects, albeit among different units of observations (see Marsden and Friedkin 1993 for examples). In both cases proximity or connectedness is assumed to facilitate the direct flow of information or influence across units. Individuals or organizations are also more likely to be influenced by the actions, behaviors, or beliefs of others that are proximate on different dimensions, including geographical and social space. 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 (e.g., Land and Deane 1992).[8]

EXAMPLES FROM CRIMINOLOGY

Much of the spatial analysis of crime can be traced back to the unprecedented increase in youth involved gun violence of the late 1980s and early 1990s. Scholars and writers in the popular media were quick to start talking in terms of this being a "homicide epidemic." Within the public health framework, an epidemic is simply defined as non-linear growth of events that typically spread within a sub-population of susceptible individuals. Using existing data sources (SHR, Chicago Homicide Data, etc.) as well as a set of city-specific micro-level homicide data that were collected in part, or in whole, by the National Consortium on Violence Research (NCOVR)[9] in such cities as Houston, Miami, Pittsburgh, and St. Louis, it was easy for researchers to demonstrate that

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[8] In addition to the advances made by spatially oriented scholars such as Anselin (1988) and Ord (1975), much of the methodological and empirical foundation currently used in spatial analysis was developed by scholars pursuing properties of "network autocorrelation models" (Doreian and Hummon 1976; Doreian 1980).

[9] The National Consortium on Violence Research (NCOVR) at Carnegie Mellon University was supported under Grant SBR 9513040 from the National Science Foundation.

homicide rates did increase in a non-linear fashion (e.g., Cohen and Tita 1999; Rosenfeld, Bray and Egley 1999; Griffiths and Chavez 2004) at the local level.

Along with these neighborhood-level studies, research at the national level (Blumstein and Rosenfeld 1998; Cork 1999) and the county level (Messner et al. 1999; Baller et al. 2001; Messner and Anselin, 2004), have consistently demonstrated two things. First, the subpopulation at greatest risk of homicide victimization during the epidemic was comprised of young urban minority males. Second, homicides exhibit a non-random pattern of with similar levels of violence cluster in space. Furthermore, the concentration of high violence areas typically occur within disadvantaged urban communities.


*Gangs, Drugs, and Exposure to Violence*

As noted above, spurred on by the youth homicide epidemic, there was a considerable increase in the number of published studies that explore the spatial distribution of violent crime, in general, and homicide, in particular. Researchers began to map homicide in an effort to identify susceptible populations, and to determine if the observed patterns of events where at least consistent with spatial diffusion/contagion. From these studies it was concluded that homicide and violence exhibit strong patterns of spatial concentration.

The presence of positive spatial autocorrelation has been interpreted as evidence of contagion. It is generally accepted that as violence increased during the last epidemic certain neighborhood level social processes or "neighborhood effects" were responsible for the geographic spread and ultimately the concentration of violence in disadvantaged

areas.  This conclusion rests heavily upon two facts.  First, even after controlling for the socio-economic composition of place, patterns of spatial concentration remain. Second, those studies which have examined local spatial patterns of violence over time do find evidence of diffusion (Cohen and Tita 1999; Griffiths and Chavez 2004.) Though no definitive answer has emerged as of yet to the question of why violence displays certain spatial patterns, several explanations have been put forth. In general, researchers have focused on the impact of "exposure to violence" (including subcultural explanations) as well as the particular dynamics and structure of violence involving illicit drug markets and/or violent youth gangs.

Viewing exposure as the social process that is responsible for the spatial clustering of violence has its origins in subcultural explanations of violence. Loftin (1986) was the first to argue that the spatial concentration of assaultive violence and its contagious nature was the result of certain subcultural processes. His use of the term "subcultural" refers to a process wherein violence spreads throughout the population as the result of direct social contact. He argues that a small increase in violence can result in an epidemic in two ways. First, an epidemic results 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. As more pre-emptive assaults occur, even more people take pre-emptive actions thereby feeding the epidemic.

Secondly, 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 number of individuals in the fight" (Loftin 1986: 555). Loftin states this process relies upon direct social contact and implicitly suggests that the concentration of violence must be the result of the limited geographic scope of social interactions. However, one could also easily imagine instances where the victims and offenders interact at schools, entertainment districts, or possibly at the types of "staging grounds" where young men battle for respect within the realm of the "code of the streets" (Anderson 1999).

The retaliatory nature of gang violence along with the violence associated with drug markets have also been offered as explanations for spatial patterns of violence. As noted by Tita and Greenbaum (2009), these explanations are basically extensions of the above arguments in that they represent "exposure" to a particular type of violence. That is, rather than exposure to violence leading to a cultural norm that shaped individual behaviors, it was exposure to the structural features of drug markets and urban street gangs that contributed to the escalation and concentration of violence.

Several features of drug markets, especially open-air markets selling crack-cocaine, make them obvious candidates in explaining 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

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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. Though these arguments are certainly plausible, the supporting evidence is mixed. Though Cork (1999) finds that the spatial and temporal patterns of the increase in violence mirror the emergence of crack cocaine markets in various regions of the nation, studies in Pittsburgh (Cohen and Tita 1999b), and another examining both Chicago and St. Louis (Cohen et al. 1998) find little evidence that drug homicide increased levels of violence or drove local patterns of diffusion.

Two important features define gangs that make them especially suitable candidates responsible for diffusion (Decker 1996). First, they are geographically oriented. The turf or "set space" where urban street gangs come together to be a gang is a well defined, sub-neighborhood area that remains consistent over time (Klein 1995; Moore 1985, 1991; Tita et al. 2005). Second, urban street gangs are linked to other gangs via rivalry networks. As we note below, research has demonstrated (Tita and Greenbaum 2009; Radil et al. 2010; Tita and Radil 2011) that it is precisely the geography of gangs and their social networks that present a set of structural properties researchers can exploit to better understand the spatial patterns of gang violence.

Below we provide a brief review of the extant literature from criminology and public health that have employed spatial regression models. Though not meant to represent an exhaustive review of this burgeoning literature, these studies do represent some of the most widely-cited articles in the field. After summarizing the findings and

the methods, we make the case for the importance of carefully modeling processes of influence into one's spatial weights matrix (*W*).


*Empirical Studies of Crime Employing Spatial Regression*

In what is widely recognized as the first attempt to explicitly model the spatial effects inherent in the production and impact of violence, Morenoff and Sampson (1997) examine the impact of violence on residential change in Chicago. They argue that in addition to reacting to the level of violence in one's own neighborhood, residents also react to the levels of violence around them. Thus, among controlling for the socio-economic measures as well as the trends in terms of residential transition, the authors also include a spatially-lagged independent variable in their model to capture the "*spatial diffusion* of homicide" (Morenoff and Sampson 1997: 56). Indeed, their findings show that the impact of homicide on population changes will differ in a focal tract depending upon the level of homicide in nearby tracts.

Morenoff, Sampson and Raudenbush (2001) examined the spatial distribution of violence more directly. It is this work that lays out the "exposure" and "diffusion" arguments. They argue that homicide may be spatially clustered because the measures associated with violence (e.g, poverty, population density, etc.) are spatially and temporally clustered, thus exposing residents who live in close proximity to each other to the same set of to the same set of conditions. Additionally, the social interactions that result in violence are likely to involve "…networks of association that follow geo-graphical vectors" (Morenoff et al. 2001: 523) along which violence is likely to diffuse. Specifically, they mention the retaliatory nature of gang violence and the fact that

homicide is likely to be committed within groups of individuals known to one another. Their final conclusion is that the spatial effects in their models are large in magnitude and that ecological models of crime that focus only on the internal characteristics of the unit of observation (census tract) are likely to suffer from misspecification. Though they find that "space" matters, and that it matters over various spatial regimes (controlling for race of a neighborhood), the precise reason it matters is less clear. As the authors note, they are "…unable to pinpoint the relative contributions of exposure and diffusion" (Morenoff et al. 2001: 552).

Rosenfeld, Bray and Egley (1999) estimated a spatial lag model to determine if the patterns of "gang-motivated" homicides differed compared to non-gang youth homicides as well as homicides that involved gang members but lacked any specific gang motivation. Three separate equations are estimated using count data and also including the spatial lag of the count in surrounding census tracts as an explanatory variable. What they find is that controlling for neighborhood characteristics, only the spatial term in only the gang-motivated analysis is statistically significant. The authors see this as evidence of gang-motivated homicides being contagious in nature and that "…the spatial distribution of gang-motivated homicide may reflect intrinsic features of the phenomenon and not simply the presence of facilitating neighborhood characteristics" (Rosenfeld et al. 1999: 512).

Smith et al. (2000) examine diffusion and spatial effects within the context of street robbery. Once again, we see that amount of street robbery in neighboring areas (census block faces) impact the level of street robbery on a focal block face. The authors conclude that the spatial effect is consistent with diffusion resulting from the spatial

bounds of the "awareness space" (Brantingham and Brantingham 1981) of offenders. Drawing upon the existing "journey to crime" literature, the authors cap awareness space so that only levels of crime in block faces within one mile of the focal block face are accounted for in the spatial weights matrix.

Gorman et al. (2001) examine the effects of alcohol outlets on violent crime rates in Camden, New Jersey. Using census block groups at the unit of analysis, Gorman et al. make a methodological argument using a spatial regression model as they identified significant positive spatial autocorrelation in crime rates and offer two spatial models: a spatial error model and a spatial lag model. However, for the lag model, Gorman et al. produce spatial lags of the independent variables rather than of the dependent variable (crime rates). While there is little explanation offered for this modeling choice, the results of the independent variable lag model suggest to the authors that while some explanatory variables in surrounding areas had a significant impact on crime rates in a given unit, the density of alcohol outlets in neighboring areas had no significant impact on crime rates. Gorman et al. find this as evidence that the effects of alcohol outlets on violent crime are highly localized and spatially concentrated and that such effects decay quickly with distance.

Kubrin and Stewart (2006) investigated relationships between neighborhood context and recidivism rates of ex-offenders in Portland, Oregon. Although not expressly interested in spatial diffusion, Kubrin and Stewart attempted to control for spatial autocorrelation in recidivism rates across neighborhoods (measured by census tracts) by including a spatially-lagged recidivism variable in their multi-level model. However, due to the limitations of incorporating spatial effects into multi-level models, they were

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unable to determine if the spatial dependence in the rate of recidivism is evidence of diffusion or due to other effects, such as spillovers.

Hipp, Tita and Boggess (2009) examine patterns of intra- and inter-group crime in an area of Los Angeles, CA that has undergone significant residential transition taking it from majority African-American to majority Latino over the last two decades. Their goal is to understand the impact of this transition on both within-group and across-group violence. To control for spatial effects, they estimate a model that includes spatially lagged predictors. Following the lead of Elffers (2003) and Morenoff (2003), they argue that explicitly modeling the spatial process through the lagged independent variables (median income, change in race/ethnicity, and income inequality between racial/ethnic groups) is theoretically superior to a spatial lag model. They contend that to "estimate a spatial lag model we would need to argue that the level of either intra- or inter-group crime in a neighboring area has a direct "contagion" effect on crime in a focal area. We do not believe this is the case, especially with respect to inter-group crime events" (Hipp et al. 2009: 41) Instead, they hold that spatial impacts may best be modeled through "…the racial/ethnic composition of adjacent neighborhoods (as these group compositions could affect inter- and intra-group crime rates in the tract of interest), how that racial/ethnic composition has changed, the income level of adjacent neighborhoods (which might create additional stress or protective effects), and economic inequality in adjacent neighborhoods" (Hipp et al. 2009: 41) They employ a weights matrix that captures a distance-decay functions truncated with a two-mile cutoff. That is, the spatial effect goes to "0" for all census block groups beyond two miles. To summarize, they find that the level of income inequality in surrounding areas has a significant impact on inter-

group violence in a focal tract as does the degree to which racial transitioning from African-American to Latino remains ongoing.

In contrast to the small scale studies described above, Baller et al. (2001) focused on national-level patterns of homicide aggregated to counties (see also Messner et al. 1999). Baller and his colleagues examined homicide rates against selected socio-economic characteristics for continental U.S. counties for four decennial census years (1960, 1970, 1980, and 1990) and concluded that "homicide is strongly clustered in space" in each time period at this scale. Baller et al also identified the southeastern US as a distinct spatial regime and interpreted a spatial lag model fit as evidence of a diffusion process in this region (the non-southeastern regime best fit a spatial error model, which suggested that the spatial autocorrelation in this regime was due to the presence of unmeasured variables). However, the mechanisms for such diffusion are difficult to arrive at for such macro-level studies and as Baller et al. acknowledge, there is no a priori reason to assume spatial interaction between counties on the topic of homicide and the large amount of spatial aggregation in the data likely contributes to the perceived spatial dependence (2001: 568–569).

With the exception of Kubrin and Stewart (2006), the above studies use SAR spatial models to examine a variety of phenomena and each time find a spatial story to the issues at hand. In these examples, spatial lag models were the most common choice but spatial error models were also occasionally fielded either as an exploratory technique (Gorman et al. 2001) or as a choice determined by model diagnostics (Baller et al 2001). When a spatial lag model was used in these examples, the dependent variable was selected for the lag with the exception of Morenoff and Sampson (1997), Gorman et al.

(2001) and Hipp et al (2009), all of whom lagged explanatory variables instead. This overview highlights the increasing consideration of spatial effects in ecological studies of crime at different geographic scales and points to the growing (but not exclusive) use of SAR models to incorporate such effects. However, the formal model of the connection between the geographic units that underpin these and other spatial models receive little attention in some of the examples and many of the authors use simple measures of unit contiguity or adjacency to formally model the interaction of interest. As an important but often overlooked element of spatial regression model specification we turn our attention to the spatial weight matrix, or *W*.

THE SPATIAL WEIGHTS MATRIX - W

Both SAR and network autocorrelation models estimate parameters in the presence of presumably interdependent variables (Anselin 1988; Leenders 2002). This estimation process requires the analyst to define the form and limits of the interdependence and formalize the influence one location (or network node) has on another. In practice, this is accomplished by identifying the connectivity between the units of the study area through a $n \times n$ matrix. The matrix is usually described as a "spatial weight" or "spatial connectivity" matrix and referred to in the SAR models as "*W*". This *W*, or matrix of locations, formalizes a priori assumptions about potential interactions between different locations, defining some locations as influential upon a given location and ruling others out.

A simpler way of describing this is that *W* identifies, in some cases, who is a neighbor and who is not, or with whom an actor interacts. This notion of influence across

space is addressed in an empirical sense by criminologists when deciding whether two geographic areal units are contiguous based upon borders or near enough for influence based on distances. However, the construction of $W$ is more than just an empirical choice about neighbors. It is a theoretical decision regarding the processes being discussed and one that has implications for the statistical estimates generated. Whether it is geographical or network space, $W$ is used to represent 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: 26) notes:

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

Following Leender's point, discussions about the nature of $W$ and how different specification choices may affect regression results have indeed been underemphasized in most spatial analytic literature: the relatively few examples to the contrary include Florax and Rey (1995) and Griffith (1996). Despite these noteworthy efforts, Leenders (2002: 44) is correct in his assessment that "the effort devoted by researchers to the appropriate choice of $W$ pales in comparison to the efforts devoted to the development of statistical and mathematical procedures." The net effect of this lack of attention is that theoretical conceptions about the role space plays in producing empirical patterns in a given dataset are often afterthoughts. Hence, the vision of a "spatially integrated social science" (Goodchild et al. 2000) for criminology remains unfulfilled, because when space is included in the analysis of crime or other social processes it is often added in a default form without consideration of the processes in question.

Such an attention deficit is a cause for concern as the products of the SAR models are quite sensitive to the specification of *W*. For example, using simulated data, Florax and Rey (1995) conclude that misspecification of *W* can affect the outcome of spatial dependence tests, such as the commonly-used Moran's *I* test of spatial autocorrelation, and of estimates of variables in spatial regression models. Griffith (1996), also using simulated data, reaches a similar conclusion, stressing that while assuming some connectivity is always more reasonable than assuming no connectivity, both under-specifying (identifying fewer connections between spatial units than really exist) and over-specifying (identifying more connections) *W* affect both regression estimates and the product of the diagnostic tests (maximum likelihood, or ML, tests) used in spatial econometrics to choose between the lag or error models.

In our review of the models used in the studies outlined above, we find that without exception, each specification of *W* is based either on simple contiguity, *k*-nearest neighbors, or the use of distance decay metrics. Although challenging, more careful modeling of spatial processes through the spatial weights matrix is of critical importance to understanding the black box of neighborhood effects emphasized by Cohen and Tita (1999a). As previously described, network autocorrelation models involve a similar challenge to spatial models and the network literature offers useful parallels to the challenge in modeling spatial dependence and interaction. In modeling dependence among nodes, social network analysts often begin with a particular social process in mind and then carefully model that process into the network autocorrelation matrix. For example, edges among nodes may be predicated upon specific social relationships (e.g., friendship, familial, or instrumental ties) or shared membership into formal/informal

groups. Alternatively, one can decide that a pair of nodes is connected only when they are similar along some particular dimension such as race, sex, income or "status" (see the discussion of Mears and Bahti (2006) below). These types of important differences can lead to very different specifications of the weights matrix.

Social scientists have employed social network analysis in an effort to explain a number of social processes, most notably the diffusion of innovations, technology, and information among individuals, societies, and organizations (e.g., Coleman, Katz, and Menzel 1966; Rogers 1983; Grattet et al. 1998). In defining underlying processes of contagion/social influence, network scientists carefully differentiate between social processes of influence that operate through direct ties or association among actors (referred to as "communication" or "structural cohesion") versus contagion that occurs among individuals who occupy shared positions within a network (referred to as "comparison" or "equivalence"). The decision to choose one process over another – communication versus comparison – is dependent upon one's chosen theory. As Leenders (2002: 26) succinctly states, "Change one's theory, change $W$."

To highlight the importance of specifying a $W$ that is consistent to with the social process of choice, we draw upon a classic example from the networks literature dealing with the question of why and when certain physicians adopted a new medical innovation (tetracycline). Coleman, Katz and Menzel (1966) posited that peer effects mattered, and demonstrated the importance of structural cohesion or direct social ties in determining who adopted the new drug, and the order in which it was adopted. That is, once a couple of doctors of "higher status" assumed the role of "early adopters", the next wave of adopters was comprised of the initial adopters' friends. Decades later Burt (1987) offered

an alternative hypothesis in which he argued that individuals are often most strongly influenced by the actions and behaviors of rivals and competitors and not by their friends. He reanalyzed the data and demonstrated that network position (as measured by "structural equivalence") was the defining predictor of adoption. Burt concluded that friendship, or any form of direct communication, had little to do with the pattern of adoption. Instead, doctors who held similarly high positions of "status" (e.g., subscribed to the multiple medical journals, were younger, made many house calls, kept up on scientific advances) within the medical community adopted earlier than did older doctors, those who spent more time with their patients than keeping up with medical advances, and who subscribed to fewer professional journals. Though neither the line of inquiry (adoption of an innovation/diffusion) nor the methodology (network autocorrelation models) ever changed, the theory employed in the research did.

MOVING BEYOND SIMPLE CONTIGUITY/DISTANCE BASED SPECIFICATIONS OF $W$

Recently, in order to better capture specific processes or patterns of influence, criminologists have begun to explore alternative specifications of the weights matrix that move beyond simple contiguity or distance. Mears and Bhati (2006) build off the long-standing finding that resource deprivation is positively associated with local levels of violence by asking whether the level of resource deprivation in other counties could influence violence in a focal neighborhood. In addition to controlling for the level of disadvantage in surrounding communities, the authors also construct weights matrices based upon the level of "social similarity" between places. The authors smartly point out

that what happens in focal neighborhood might only influence events in other neighborhoods if there is a mixing of the population between the two places. Though the research does not actually have network data linking the friendships and communication across place, they reason on the bases of "homophily" (Blau and Blau 1982; McPherson, Smith-Lovin and Cook 2001) that social interactions are more likely among "similar" individuals. Using various measures of resource deprivation to construct alternative measures of $W$, controlling for both resource deprivation in surrounding neighborhoods (as well as controlling for spatial lags of homicide, the dependent variable) they find that geographic as well as "social proximity" to resource deprivation was associated with higher homicide rates. Furthermore, social proximity, or nearness in terms of social similarity, had a much stronger impact than did geographic proximity alone. An interesting finding from their research is that while these results held for both instrumental and expressive types of homicides, no effect was found with regard to gang-related homicides. For that insight into this finding, we turn to a recent set of studies looking specifically at gang violence.

In an effort to better understand the spatial distribution of violence involving gang members, Tita and Greenbaum (2009) and Tita and Radil (2011) also examine spatially proximate effects of violence as well as violence in socially proximate communities. This body of research lays out a very clear hypothesis regarding how gang violence in one area might influence gang violence in other areas. By exploiting the spatial nature of gangs (they hang out in specific areas, known as "set space" (Tita et al., 2005)), and the social dynamics of gangs (they are linked to other gangs through a network of rivalries), they hypothesize that the violence in a focal area will have a stronger impact on violence

in areas that are linked through the socio-spatial dimensions of the gang rivalry network than will spatial contiguity alone. In fact, the studies in Los Angeles, CA (Tita and Radil 2011) and in Pittsburgh, PA (Tita and Greenbaum 2009) both demonstrate support for this hypothesis. That is, the purely geographic nature of "diffusion" was muted when one controlled for whether or not proximate (or non-proximate) areas (block groups) were linked by containing the set space of rival gangs. The authors of both studies are careful to point out that they constructed their weights matrices with a specific process in mind – the transmission of violence through a gang rivalry network – and caution that had they been interested in looking at other types of violence (e.g., drug violence, domestic violence) their particular "social similarity matrix" would have been inappropriate.

SUMMARY

The use of spatial regression has clearly advanced our understanding of crime patterns at both the local (neighborhood) and county level. We include Table 2.1 as a summary of both the traditional and the more creative research examining spatial effects. Summarizing the table, we know that whether for recidivism, homicide, gang violence, or robbery, there is evidence for spatial dependence and possible spatial interaction processes at work. We also know that addressing the spatial autocorrelation present in most aggregated crime data offers more reliable modeling estimates and that attempting to understand the substantive sources of spatial dependence in the social processes of crime leads is a critical step in model specification. However, as Table 2.1 demonstrates, our thinking and operationalization of the spatial processes has, until recently, remained at the level of only accounting for connections between units in the simplest of

geographic terms. Complex theoretical stories about the mechanisms of diffusion between places can quickly become lost in a spatial weight matrix that uses the simplest conceptions of geography (simple measures of adjacency/contiguity, or distance such as Rook/queen's contiguity, linear distance decay functions, or *k*-nearest neighbor) to specify the nature of interaction, including scope, direction, and intensity. As there remains no statistical method capable of estimating the 'best fit' of a spatial weight matrix to one's data (Leenders, 2002: 38), embodying theory into the specification of *W* is the only sensible recourse available.

A recent article by Sampson and Sharkey (2008) examined intra-urban movement patterns of 4,000 families in Chicago between 1994 and 2002. The take-away point of this research is that there is great disparity in the types of places that people move to, and that where people move can be explained by controlling for race and economics. While there is evidence that poor whites or poor Latinos will move into non-poor neighborhoods that may contain a sizable white population, the mobility of blacks along all levels of income is restricted among existing predominately black neighborhoods. Non-poor blacks rarely move into other non-poor areas comprised of non-blacks, and while some poor blacks may move into non-poor black communities, the vast majority of moves for poor African-Americans are into other poor black neighborhoods. We highlight this research because it provides the richness of data to truly understand the socio-spatial nature of influence. From these findings, it seems evident that incidents of violence in poor black neighborhoods are far more likely to diffuse into other poor black neighborhoods than in surrounding, non-black (poor or otherwise) neighborhoods. In this regard, it confirms the assumptions of Mears and Bhati (2006) regarding the connectivity

among places based on social similarity, but the level of detail in this study far exceeds the use of resource deprivation as a proxy for social interaction.

We think that Sampson (2008) said it best noting that "The advent of GIS modeling and new data sources on social interactions and networks of spatial connection are revealing the profound spatial ordering of a bewildering array of urban phenomenon." If we want to tackle the question posed by Cohen and Tita (1999a) that motivated this chapter, researchers need to exploit these types of data sets to truly understand the processes by which violence diffuses across space.

Table 2.1: Summary of Empirical Studies using Spatial Regression in the Study of Crime

| Author | Topic | Model Type | Estimation | Specification of *W* | Conclusions |
|---|---|---|---|---|---|
| Morenoff and Sampson (1997) | Effects of violence on residential change; contagious nature of residential change | Spatially lagged dependent variable (Wy) using residential change along with spatially lagged independent variables (Wx) using homicide rate | 2-stage least squares using the spatial lag of "residential change potential" (Wy) and the "homicide potential (Wx) explanatory variables in the second-stage of estimation | Distance decay, weighted by distance from centroid | Impact of homicide on population changes will differ in a focal tract depending upon the level of homicide in nearby tracts |
| Morenoff et al. (2001) | Spatial distribution of homicide crime | Spatially lagged dependent variable (Wy) | Maximum-likelihood estimation using a two stage approach – Step one estimates a log-homicide rates while the second step includes a spatial lag of the estimated rate | Rook's case geographic contiguity (shared border lengths) | Spatial dependence in levels of violence persists controlling for community disadvantage as well as "collective efficacy." |
| Rosenfeld et al. (1999) | Spatial distribution of gang-motivated, gang-affiliated and non-gang youth homicide | Spatially lagged dependent count variables (Wy) | Maximum-likelihood estimation of count models | Inverse distance across all space | Gang-motivated homicide shows greater spatial dependence, suggesting contagious nature of these types of events |
| Smith et al. (2000) | Spatial effects of street robbery | Spatial lagged dependent variable (Wy) | Generalized negative binomial regression | *K*-nearest neighbor variant: sample of 20 face blocks within 1 mile radius of focal block; sample limited to only two directions (either n/s or e/w from focal block) | Street robbery in neighboring areas (census block faces) impacts the level of street robbery on a focal block face |

Table 2.1: Continued

| Author | Topic | Model Type | Estimation | Specification of *W* | Conclusions |
|--------|-------|-----------|-----------|---------------------|-------------|
| Baller et al. (2001) | County level spatial patterns of homicide | Spatial regimes; Spatial error and spatially lagged dependent variable (Wy; We) | Maximum-likelihood: Robust Lagrange Multiplier tests | *K*-nearest neighbor (all counties connected to exactly 10 nearest (by centroid distance) neighboring counties) | South US region shows evidence of homicide diffusion; spatial dependence in non-South likely due to unobserved variables |
| Gorman et al. (2001) | Effects of alcohol outlets on violent crime rates | Spatial error and spatially lagged independent variables (Wx, We) | Maximum likelihood | Queen's case geographic contiguity (shared border lengths and/or border points) | The density of alcohol outlets in neighboring areas had no significant impact on crime rates in focal units. |
| Mears and Bhati (2006) | Spatial distribution of homicide, by type | Spatially lagged dependent variable (Wy); Socially lagged dependent variable; Social and spatially weighted independent variables (Wx). | Negative Binomial using natural log of homicide counts | Geographic space is measured using queen's case contiguity; Social space is measured by comparing measures of social similarity (including resource deprivation) between each pair of communities. The similarity matrix decays exponentially as dissimilarity increases. | With the exception of gang homicide, social similarity among geographic units is more strongly related to homicide than is geographic adjacency. |
| Kubrin and Stewart (2006) | Effects of neighborhood context on recidivism rates | Multi-level model (included a spatial lag variable) (Wy) | HLM with the inclusion of a spatially lagged measure of recidivism rates. | Queen's case geographic contiguity | Spatial dependence in recidivism; unable to assess evidence for diffusion |

Table 2.1: Continued

| Author | Topic | Model Type | Estimation | Specification of *W* | Conclusions |
|--------|-------|-----------|-----------|----------------------|-------------|
| Tita (2006); Tita and Greenbaum (2009) | Spatial distribution of Gang violence | Spatially lagged dependent variable (Wy); Socially lagged dependent variable | "Anselin-alternative Method" using the "violence potential" as an instrumental variable in 2-stage estimation | Geographic space is measured using queen's case contiguity; Social space is constructed using the location of gangs in space, and the rivalry network that links them socially | Spatial dependence is best modeled by considering the socio-spatial distribution of gang rivalries, which extend beyond contiguous neighbors. |
| Hipp et al. (2009) | Intra-group and Inter-group Violence | Spatially lagged independent variables (Wx) | Negative Binomial with spatially lagged X's | Distance decay, 2 mile maximum | Clear evidence of income inequality and racial transition in surrounding tracts impacting inter-group violence in focal tract |

Figure 2.1: Spatial data may demonstrate a pattern of positive spatial autocorrelation (left), negative spatial autocorrelation (right), or a pattern that is not spatially autocorrelated (center). Statistical tests, such as Moran's *I*, should always be used to evaluate the presence of spatial autocorrelation.
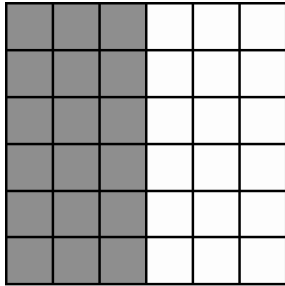


Positive spatial autocorrelation
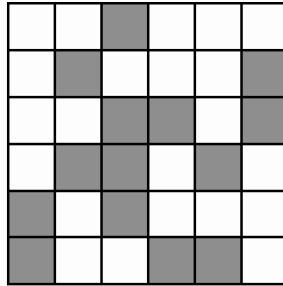
No spatial autocorrelation
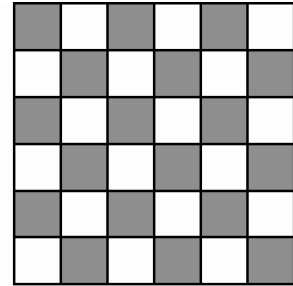
Negative spatial autocorrelation

**CHAPTER 3**

**THEORIZING SPACE AND PLACE FOR SPATIAL
ANALYSIS IN CRIMINOLOGY**

This chapter is drawn from a conceptual essay published in a special issue of the *Journal of Quantitative Criminology* (Tita and Radil 2010a) and presents a theoretical framework for understanding and modeling context that builds on the place concept in geography that emphasizes connections between places. Therefore this essay may be seen as akin to a theory chapter in a traditional dissertation format and is offered in that spirit. It is presented here in a slightly altered form from Tita and Radil (2010a) to avoid duplication with the previous chapter.

INTRODUCTION

In this essay, we attempt to better understand the role that place plays in explaining the spatial distribution of crime. We briefly explore the relevant criminological literature beginning with the works published in the last decade and comment on the important contributions and advances achieved since then. Though a formal review of the voluminous literature even on this subset of spatial analysis is far beyond the scope of this paper, we do try to highlight some of the more seminal findings along with more recent works that employ innovative approaches to understanding the spatial distribution of crime. In terms of advancing the field of spatial analysis, we focus on two important issues that are beginning to garner increasing attention within the crime literature: Defining and measuring "place" and the adoption of more deductive models that attempt to capture particular processes of influence in the specification of the spatial weights matrix, represented as $W$.

Clearly the development of important theoretical constructs related to the ecology of crime far pre-date the availability of user-friendly, off-the-shelf mapping and spatial analysis software. However, it would be very difficult to overstate the important role these tools played over the last decade in terms of advancing our understanding of the spatial distribution of crime. The mapping of crime incident data permits one to explore how the built environment, the presence of certain types of businesses or activities, or characteristics of the local residential population impact the observed spatial distribution of crimes. The impact of bars, public housing or illicit activities such as gangs or drug markets on local patterns of crime has been of particular interest (Tita and Ridgeway 2007; Taniguchi et al. 2011). One can also determine how the spatial distribution of crime changes over different time scales. For instance, in the short term, one might be interested in determining how the policing of drug markets or gang areas might impact the spatial distribution of crime (e.g., Braga 2001; Tita et al. 2003). In fact, using GIS and spatial analysis in the evaluation of such place-based policing strategies has resulted in the robust conclusion that crime does not "move around the corner" and that rather than a displacement effect, we often see a diffusion of the benefits of place-based policing to adjoining areas (Bowers and Johnson 2003; Weisburd et al. 2006). One can also look over longer time periods, and at larger units of analysis, to examine the relationship between changes in the socio-economic composition of local neighborhoods and the spatial distribution of crime (Cullen and Levitt 1997; Morenoff and Samspon 1997; Hipp et al. 2009).

It is worth noting that the term "spatial analysis" applies equally to the study of incident level point patterns (e.g., crime hot spots) as well as to the study of aggregated

crime counts or rates at the area level (e.g., spatial autocorrelation among census block groups, tracts, or "neighborhoods"). For our purposes, we focus solely on the spatial analysis of crime at the aggregate rather than the incident level.[10]

ECOLOGICAL STUDIES OF CRIME – THE USE OF SPATIAL REGRESSION MODELS

In a review of the growing use of spatial approaches in criminology, Cohen and Tita (1999a) noted that the growing spatial analysis of crime literature was enabling criminologists to move beyond simply mapping crime and demonstrating that crime does indeed cluster in space. Indeed many studies over the last two decades have begun to seriously consider why crime clustered in space and search for evidence of diffusion across space (e.g., Morenoff and Sampson 1997). In the time since Cohen and Tita (1999a), spatial regression models were often used in an attempt to construct, inductively, explanation for the observed patterns of spatial clusters. In addition to crime, researchers began to use spatial regression models to demonstrate that many negative health issues including, but not limited to, low birth weight (Morenoff 2003), infant mortality (Rushton et al., 1996), and depression (Ross 2000) also cluster spatially (for a complete review of the neighborhood effects literature see Sampson et al., 2002). From these studies emerged a consistent set of explanatory variables that characterize "bad" neighborhoods (e.g., concentrated poverty, stability of residents, female headed households, minority

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[10] We would be remiss if we did not mention two areas of growing importance. Trajectory models are being employed by a number of researchers to examine the "criminal careers" of communities (Weisburd et al. 2004; Groff et al. 2009). Griffiths and Chavez (2004) used this method to focus specifically on the issue of diffusion. Second, there have been two recent publications within the criminology literature (Cahill and Culligan 2007; Graif and Sampson 2009) that argue for the primacy of Geographically Weighted Regression (GWR) over "global" regression models. GWR differs in that it does not assume stationarity, thus coefficients are permitted to vary over different regions of one's study area.

population), and that there appeared to be an aggregate effect, dubbed a "neighborhood effect," to living in these places. For instance, concentrated poverty negatively impacts all residents of a community regardless of one's own level of personnel income. That such places also cluster in space suggests that neighborhoods are not independent units of observation. On one hand the lack of independence might simply be a result of the clustering of important variables such as race and poverty in space. On the other hand, it was posited that there might be forces at work that make the level of crime in one neighborhood dependent upon the actions and activities occurring in other areas (Sampson 2004; Morenoff et al. 2001). That is, social processes might be at work that result in the diffusion, or contagion of crime, across space over time (for a discussion of the types of diffusion and contagion, see Cohen and Tita 1999).

In trying to further understand the patterns and the spread of violence, spatial regression (or spatial econometrics) quickly became, and remains, the methodology of choice. As noted above, spatial autocorrelation occurs when the values of variables sampled at nearby locations are not independent from each other. This lack of independence makes the use of OLS regression techniques inappropriate. While there are a variety of methods to address spatially autocorrelated data, simultaneous autoregressive (SAR) models have become the most popular, especially spatial error models and spatial lag (or "dependence") models (see Tita and Radil 2010a).

Spatial error models are appropriate for modeling unobservable processes (e.g., norms or beliefs) that are shared among individuals residing in proximate places, or when the boundaries that separate "places" are arbitrary to the extent that two "different" places

are actually very similar across various social, economic, or demographic features (i.e., the clustering of like places). The spatial error models takes the following form:

$$Y = X\beta + \varepsilon; \varepsilon = \lambda\varepsilon + u, \text{with } E[u] = 0, E[uu'] = \sigma^2 I,$$

where $\varepsilon = W\varepsilon$, and $W$ is the ($N$ x $N$) autocorrelation weighting matrix that contains information about which spatial units (e.g., census tracts, neighborhoods) are spatially connected and $\lambda$ measures the spatial correlation of the error term. In the absence of correlation among neighbors' error terms, the $\lambda$ equals zero therefore using OLS methods is appropriate. Failure to account for the non-dependence in the error will still yield unbiased coefficients; however, estimates of the standard errors on those coefficients will be incorrect (Anselin 2002).

When the level of crime in one neighborhood is directly dependent upon the activities or social processes occurring in a neighboring area, one must apply a spatial lag (spatial dependence) model. Failure to consider spatial dependence in one's model is far more serious than ignoring spatially autocorrelated error terms because the model is mis-specified and the estimates of the coefficients are incorrect. The spatial lag model takes the form:

$$Y = \rho WY + X\beta + \varepsilon, \text{ with } E[\varepsilon] = 0, E[\varepsilon\varepsilon'] = \sigma^2 I,$$

where $\rho$ is the spatial coefficient on the spatially lagged dependent variable, and it will be nonzero if outcomes in one location influence outcomes in another location. $W$ is once again the ($N$ x $N$) autocorrelation weighting matrix.

The autocorrelation matrix, $W$, is what adds a spatial dimension to the above models allowing the researcher to define which spatial units are related. Though formal statistical models of spatial autocorrelation are relatively new, most crime researchers

continue to rely on the specification of one's spatial weights matrix, *W*, using either

spatial contiguity/adjacency or by employing measures of distance decay. The decision to

employ such measures is consistent with Tobler's First Law of Geography (Tobler 1970),

which states that "Everything is related to everything else, but near things are more

related than distant things." Our goal is not to refute this assertion or criticize studies that

continue to rely on weights matrices specified in this manner. In fact, there are plenty of

theories to support the notion that crime in a focal area influences the amount of crime in

immediately proximate areas and in such cases, this is the correct specification of how

space matters in *W*. However, we do want to highlight innovative attempts to model

crime by recognizing that crime in a focal area may directly influence crime in

geographically distant areas.

As we have noted elsewhere (Tita and Greenbaum 2009; Tita and Radil 2010b),

the selection of which model, error or lag, has, and continues to be, driven by conducting

goodness of fit tests rather than theory.  Similarly, in the case of the estimate of spatial

lag models, the conventional approach has been inductive by nature as post-hoc

explanations of why "space matters" are constructed after the models are estimated.

Again, as with the specification of *W* by only considering strictly geographic notions of

space, we do not want to be overly critical.  Empirical exercises to choose one's model

and inductive reasoning have added tremendously to the collective understanding of the

diffusion of violence.  However, as Radil et al. (2010) cautions, it is important to remain

vigilant against a sort of "spatial fetishism" in which the ability to simply map crime

patterns takes precedence over attempting to explain the causes of the clusters. That is,

"When spatial analysis is overly dependent on reasoning from spatial form to social

process, the risk of reducing people to the spaces they occupy grows while the likelihood of new insights shrinks" (Radil et al. 2010: 308).

As noted above, the theme of diffusion for the Special Issue was motivated by the unprecedented growth in levels of youth homicide during the late 1980s through the early 1990s. As a result, criminologists began to adopt an epidemiological framework and speak of the contagious diffusion of violence. The simple descriptive analysis of homicide data showed that urban minority males killed with guns represented the subpopulation at greatest risk for victimization. The combination of exploratory spatial data analysis and spatial regression analysis found evidence in support of the conclusion that violence was diffusing at the national level (Blumstein and Rosenfeld 1998; Cork 1999; Kellerman 1996), county level (Messner et al. 1999; Baller et al. 2001; Messner and Anselin 2004), and local levels (Block and Block 1993; Cohen and Tita 1999; Fagan et al. 1998; Kennedy and Braga 1998; Klein et al. 1991; Morenoff et al. 2001).

As we have noted elsewhere (Tita and Radil 2010b), these early studies were important because they began to hint at the structures and underpinnings of social processes that might help us understand why violence diffuses across space. Collectively, these studies also found that the clustering of violence is better explained using spatial lag models (i.e., the result of an unobserved pattern) rather than spatial error models (i.e., the result of the clustering of covariates). By examining the statistically significant coefficient on the spatially lagged dependent variable, specific explanations were offered regarding the forces driving the spread of lethal violence within urban settings. Most frequently, the explanations offered in the above studies included some (or all) elements of the proliferation of crack cocaine markets, an increase in the carrying

and use of guns by youths, and/or the emergence of urban street gangs. More recently, the impact of parolees re-entering communities on crime (and recidivism) has been examined (Kubrin and Stewart 2006).

DEDUCTIVE SPATIAL MODELS AND ALTERNATIVE MEASURES OF "SPACE"

There have been several novel attempts to capture the geographic dimensions of the forces that influence the spread of violence by offering alternative specifications of the autocorrelation matrix. These new techniques take a deductive approach to the modeling of specific social processes believed to be driving the diffusion of crime and are based in the "social influence" literature wherein social network analysis has been used to understand the diffusion/adoption of norms or innovations among individuals or organizations (see Marsden and Friedkin 1994; Leenders 2002).

In one of the first attempts to geographically "unbound" the autocorrelation matrix, Mears and Bhati (2006) model homicide by exploiting the finding that social similarity increases the probability of communication and social interaction (see McPherson et al. 2001). The researchers examined race, ethnicity and income at the tract level and linked together the tracts only if the residents were similar. They argue that events in a focal area will be influenced more strongly by events in non-adjacent but socially similar areas than in adjacent, but socially dissimilar areas. The authors find support for this argument and conclude that social distance is important. However, space also matters and the influence of violence in one area has on violence in another is especially powerful when the areas are both spatially **and** socially proximate.

Tita and Greenbaum (2009) and Tita and Radil (2011) provide examples of how the spatial and social dimensions of urban street gangs can be exploited in an inductive approach. Their research argues that gangs are likely to be especially relevant to diffusion because they are organizations that are sustained over time through continuing social interactions within specific geographic locations and because the area in which gangs hang out experience high levels of crime, especially violence (Kennedy et al. 1997; Tita and Ridgeway 2007.) Their inductive models of violence exploit social network data on gang rivalries along with the location of gang "set space" (Tita et al. 2005). Using matrix algebra, an autocorrelation matrix (*W*) is constructed wherein a non-zero value indicates that a pair of geographic units contains the set space of rival gangs. The results from studies in Pittsburgh and Los Angeles were consistent in demonstrating that the weights matrix that considers the socio-spatial nature of gangs and their rivalries provides a better fit to the data.

Different types of violence/crime will require different theories and different specifications of the spatial autocorrelation matrix.  For instance, one might model the diffusion of youth violence by considering social interactions that occur within schools. In such a case neighborhoods would be linked together if and only if they send students to the same school buildings.  Though Meares and Bhati (2006) have strong theoretical justification for modeling patterns of influence using measures of similarity, studies that capture the social networks and communication networks would provide an empirical validation of their approach. In fact, a recent publication in the journal *Science* provides an excellent template for how such a study could be accomplished.

Interested in testing the relationship between community level economic development (employment) and interpersonal social networks, Eagle et al. (2010), are able to measure the patterns of social interactions for the entirety of the United Kingdom. Each year in August, the "from" and "to" locations for over 99 percent of the land line telephone calls and over 90 percent of all cell phone calls are recorded. The researchers used this dataset to test the "strength of weak ties" argument (Granovetter 1973) by examining the level of social, economic and demographic (dis)similarity between the locations of the communicating parties. Their analysis demonstrates that communities that place calls to others who reside in places heterogeneous from their own fare much better economically.

One could imagine using geographically identified communication data for a variety of reasons within the community and crime literature, in general, in the spatial analysis, in particular. As used in the original article, the communication patterns could be used to construct community-level measures of "bridging" versus "bonding" social capital (see Tita and Boessen forthcoming). It could also be used in the construction of spatial autocorrelation matrices. One could create a simple binary matrix in which two areas were identified as "neighbors" if the number of calls linking the two areas exceeded a user set threshold. Measuring the frequency of calls between two areas would permit one to capture the strength of the link between the two communities, though this would be complicated by mobile phone technology. Using this information would result in a correlation matrix that explicitly includes a weighted measure of the potential for activities in one area to influence crime in another based not on geography, but on the social distance between places.

DEFINING PLACE FOR SPATIAL ANALYSIS

As noted above, spatial approaches in criminology have a long history of drawing upon geographic concepts, and later, geographic technologies. One particular way in which geographers and criminologists have tried to understand the behavior of social actors is through the concept of place. Place is one of the most central concepts in geography (e.g., Relph 1976; Tuan 1977; Entrinkin 1991; Sack 1997; Staehel, 2003; Cresswell 2004) and a great deal of research in spatial criminology makes use of different aspects of the place concept, albeit sometimes uncritically. As such, we begin with a discussion of the place concept, how it is used in different research traditions in geography, and how such approaches can inform current and future research in criminology.

Place seems simple enough on the surface but a great many scholars have struggled to describe and define exactly what is place. As noted by Staeheli (2003), Cresswell (2004) and others, place is a multifaceted concept and often used in different ways within different research traditions. For example, Staeheli (2003: 159) identifies different but interrelated perspectives on place within geography: place as a physical location or site; as a cultural and/or social location; as context; as something socially constructed over time; and as an ongoing process. These various elements and perspectives on place should be read as fundamentally interrelated although some are more prominent than others. For example, nearly all contemporary work explicitly involving place in human geography proceeds from assuming that places are socially constructed and are the products of human activity. From this starting point, the research

questions involving place range from ideographic approaches that emphasize the distinctiveness of a given place to those that attempt to explain such uniqueness by reference to wider political or economic processes or structural conditions (Cresswell 2004).

As noted by Staeheli (2003), understanding place as a specific physical location or an otherwise bounded site is a common approach, especially within spatial analytic traditions in geography. Expressly spatial approaches are often framed as the study of relationships that connect discrete places (e.g., Staeheli 2003). In other words, in this tradition, places are typically seen as discrete locations in a spatial setting. However, this tradition also deemphasizes the uniqueness or distinctiveness of places and a consideration of place becomes a question of research design: how to select observation locations or sites for research. Places then are defined primarily spatially. The issues focus on how locations are bounded in space, how distant sites are from each other on a spatial plane, etc.

Another approach to place familiar to the ecological tradition in criminology is to see place as context. This approach also has been important in many different subfields of geography and tends to see places as part of a broader environmental context which one must consider to fully understand human action (which of course occurs within 'places', i.e. specific locations). The characteristics of places are typically understood as potential 'variables' for a statistical/spatial analysis in this approach in geography, criminology, and many other fields of study (see O'Loughlin 2000, 2003). The place as context approach is neither new nor exclusive to geography (see for example Émile Durkheim's (1897) research on the environmental and personal factors associated with suicide). However,

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understanding place as context tells one little about the appropriate way in which to define a place or a series of places for systematic study.

These two perspectives on place are at the heart of an emerging technical discussion in criminology about the importance of considering the proper level of aggregation when estimating neighborhood effects for spatial modeling (see Hipp 2007; Wiesburd et al. 2008; Wiesburg and Braga 2010). As Hipp (2007) points out, in the ecological tradition in criminology, data is typically aggregated to geographic areas which vary in size and configuration, such as census units, which typically serve as the units of analysis for spatial models. Taking this approach to the study of crime leaves one confronted with the challenges of the modifiable areal unit problem, or MAUP (Openshaw and Taylor 1979, 1981; Openshaw 1984; see Gehlke and Beh, 1934 or Robinson 1950 for classic examples of MAUP, or Openshaw 1996 for a more contemporary review). The modifiable areal unit problem arises from the fact that areal units are usually arbitrarily determined in the sense that they can be aggregated or disaggregated to form units of different sizes or spatial arrangements (in other words, they are 'modifiable'). MAUP involves two interrelated elements, the scale problem and the zoning problem (Openshaw and Taylor 1979). Openshaw and Taylor (1979: 128) describe the scale problem as "the variation in results that may be obtained when the same areal data are combined into sets of increasingly larger areal units of analysis," and the zoning problem as "variations in results due to alternative units of analysis where $n$, the number of units, is constant." For the scale problem, increasing the aggregation of units by increasing the area covered by the units (which also typically involves decreasing the total number of units for a given area) decreases the variance in the data

between the units. For the zoning problem, rezoning the areas contained by each unit while holding the total number of units the same can impact both the mean and variance of any measured data.

These issues have important implications for ecological studies of crime as multivariate statistical analyses can be sensitive to variations in scale and zoning systems, leading to highly unreliable results (e.g., Fotheringham and Wong 1991). The problems posed for statistical inference from MAUP have led some to conclude that all methods whose results depend on areal units should be discarded and techniques independent of areal units should be used (e.g., Tobler 1989; see also Openshaw and Taylor 1981; Openshaw 1984; Fotheringham 1989; Fotheringham and Wong 1991; Fotheringham and Rogerson 1993). Grid-based models have also been advocated in spatial analysis to avoid the use of inconsistently sized areal units but the issues of the choice of grid size and the associated level of aggregated information remains. Hipp's advice is not as extreme as Tobler's (1989), but he does advocate that analysts should carefully consider whether a particular geographic unit of analysis "is actually appropriate for the outcome of interest or the structural predictors being used" (2007: 660). Given that there remains no technical solution to the problems posed by MAUP, Hipp's (2007) advocacy for theory to guide one's choice of the appropriate spatial unit of analysis is crucial.

In response to a growing recognition of the need for a careful consideration of the concept of place and of how place can be operationalized for the systematic study of crime, Hipp (2007) argues for a move toward using geographically smaller units of analysis and, correspondingly, less aggregated data in the spatial analysis of crime (see also Hipp et al. 2009). For example, Hipp (2010) describes a unit of analysis for spatial

modeling that he calls "micro-neighborhoods" which consist of around 10 households. The obvious size reference ("micro") in Hipp's (2010) unit of analysis suggests the utility of another geographic concept, that of scale, when considering the question of defining and operationalizing place for systematic analysis. Scale, which refers to the geographic scope or reach of a given phenomena (see Marston et al. 2005), is necessary to consider when attempting to specify any geographically-based unit of analysis. In other words, scale is implicated in thinking about how places are bounded in space. However, scale has also been heavily critiqued in recent debates in human geography about the nature of the concept and its utility in geographic research (e.g., Herod and Wright 2002; Mamadouh et al. 2004; McMaster and Sheppard 2004; Marston et al. 2005)

The arguments about scale focus on the geographic reach and scope of the social activities that are presumed to form places and how such scales can be and are routinely created, maintained, and marshaled by people for certain political and economic agendas (e.g., Taylor 1982; Smith 1992; Swyngedouw 2004). An important element of these critiques for this discussion is that the larger the scale that one chooses to focus upon to define a place or to otherwise bound or delimit a place, the more likely it is that the specific issue of interest can be obscured from the analyst by processes operating at various other scales and in various other places (e.g., Massey 1997). The broad point for criminology from these debates is that analysts should be ever cautious of uncritically using arbitrary or pre-given units for analysis or of assuming that such units can or should be thought of as 'places'. The reference to micro-scale units in criminology research (e.g., Hipp 2010) evokes this point and the scale/place debates in geography help draw attention toward careful and theoretically informed thinking of about places.

The move toward smaller scale units of analysis can be seen as perhaps driven by the technical issues of data collection and levels or aggregation (e.g., MAUP) but should also be one in which the insights of the scale/place debates are considered. A careful read of the technical and theoretical issues involved with delimiting space for systematic study makes it clear that it is "geographical scale that defines the boundaries and bounds the identities around which control is exerted and contested" (Smith, 1992: 66). In short, the scales used to delimit places that could be used as units of analysis are products of myriad human action and goals. Places, therefore, are never natural, preformed, or given and there is no such thing as the 'right' scale for any given research topic or interest. Hipp (2007, 2010), Hipp et al. (2009), and others are to be commended for suggesting approaches that consciously attempt to deal with the challenges posed by MAUP. But just as with grid-based approaches, the 'smaller is better' micro-scale approach to place in criminology must still wrestle with the problems of place as something that is ultimately socially constructed and therefore contested and subject to change as well as with the perhaps more familiar technical issues of MAUP.

Given the combination of the realities of the high costs of collecting data and the general availability of census data, it is unlikely and perhaps unreasonable to expect that criminologists will abandon the use of geographic units with some amount of aggregated data (such as census units). Accordingly, there are some innovative advances being undertaken which rely upon capturing the spatial dimension of social networks to define the geography of a community.[11] For example, Radil et al. (2010) and Tita and Radil

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[11] A move toward using social networks (either empirically or conceptually) is also evident in geography where concerns about the problems with scale have led some to turn to network models of social process (notable examples from a variety of geographic sub-disciplines include Cox 1998; Amin 2002; and Flint et al. 2009).

(2011) focus on territorially-based rivalry relationships as a way to capture place-to-place interactions between gangs. Using responses from a survey that asked police along with current and former gang members to identify the rivalry relationships between a set of 29 different gangs, the authors find that the complex web of rivalry relationships, some of which stretch relatively long distances over space, is an important factor that explains the spatial distribution of gang-related violence and that connections between census units based on rivalry are better predictors of the overall spatial pattern of violence than are connections based on distance or proximity.

Another example is found in the work of Grannis (2009) which posits that street and road networks shape social interaction and thus neighborhoods. Grannis refers to areas defined by interconnected small "tertiary streets." as "T-Communities" and argues that social ties form among individuals who come into physical contact with one another by walking along, or crossing tertiary streets. Grannis (2009) that unlike communities defined by boundaries drawn for administrative purposes (e.g., census tracts, zip codes), T-Communities represent a much more realistic definition of a community. By carefully examining local tertiary streets and their effect on the structure of social networks, Grannis (2009) suggests that researchers can begin to understand the process by which communities develop social capital for creating and maintaining safe communities.

SUMMARY

There have clearly been a number of important advances in the spatial modeling of crime at the aggregate, place-based level over the last 25 years. Looking back, one is

hard pressed to even identify the existence of expressly spatial analytic approaches to understanding crime until the concurrent development of and widespread access to both desktop mapping and spatial statistical software in the early to mid-1990s (e.g., desktop GIS packages and spatial software such as SpaceStat). It is clear that we have come very far in a relatively short period of time. In fact, we've come so far that it is now difficult to argue that the most pressing needs for the future of the spatial analysis of crime are either technological or methodological in nature. It is our conclusion that the most pressing issues remain to do with the sound theorization of human behavior and crime in geographic space and with making sure that the now sophisticated spatial methods that we do use are those that flow from and are informed by theory.

As it turns out, this is an old dilemma for spatial analysis. For example, it was more than 30 years ago that geographer Piers Blaikie (1978: 276) took stock of the state of affairs of diffusion research in geography and remarked that the application of sophisticated quantitative spatial techniques "has been more concerned with the techniques themselves than what they tell us about the process of spatial diffusion. The preoccupation with spatial form without an adequate theory of process has meant that the progress in technique has not been able to help progress in theory." Blaikie (1978: 276) concluded that methods should be a secondary concern "until a satisfactory theoretical framework [for diffusion] is devised." Unfortunately, things may not have changed as much as we would hope. Arthur Getis, a foundational figure in spatial analysis, recently argued that overly simplistic notions of the importance of distance to human activity (which he traces to 19th century 'least effort' theories of human activity; see also Isard (1956)) continue to underpin most spatial modeling research and that "unfortunately for

the discipline of geography, no substantial work about distance theory has occurred since the 1960s and early 1970s" (Getis 2009: 407).

From these perspectives, the challenges for future work are not those that pertain to the development of new mapping technologies or more sophisticated statistical methodologies (e.g., geographically weighted regression, the development of Bayesian methods in spatial analysis). The most pressing issues remain connected to the sound theorization of spatial human behavior. The most important developments have, and continue to occur, within the realm of theory and good science. That is, regardless of how sophisticated our methodologies become for the estimation of spatial models, the key will always be that the specification of these models be sound in terms of the measurement and definition of place and the manner in which areas are deemed "neighbors."

In using spatial regression methods to explain crime patterns, we are respectful that researchers relying on official sources of data such as the Census Bureau will forever be hamstrung by the availability of meaningful covariates that are aggregated to the appropriate level of crime. Being mindful that place is often socially constructed and that various criminological theories suggest social processes that operate at different spatial resolution is all the more important. It is also vital that, in the case of spatial lag models, one must carefully consider the full geographic extent in which the events in one area can influence events in other areas regardless of the geographic distance between them. Though the influence for a crime in a focal area in other areas might decay over distance, it is possible that there are other networks of social interactions (e.g., interactions that occur outside the neighborhood at work or school, participation in voluntary or religious organizations, adversarial networks as presented in our gang example) that make events

in one area extremely salient in the commission of future events in otherwise

geographically distant areas.

# CHAPTER 4

## MODELING SOCIAL PROCESS IN THE
## SPATIAL WEIGHTS MATRIX

This chapter, published in the *Journal of Quantitative Criminology* (Tita and Radil 2011), examines alternative specifications of the spatial weights matrix and compares more common distance-based (adjacency-based) specifications with those that are more explicitly grounded in a theory of competition between the gangs. These alternative specifications are used in spatial regression models and the impact of the different specifications on model performance is evaluated. An important finding from this chapter is that a 'hybrid' spatial weights matrix can be constructed that captures both distance-based and social relationship-based interactions. This finding leads directly to the research presented in the next chapter. This paper is presented in this chapter unaltered from the published version aside from minor formatting changes.

INTRODUCTION

Social networks are often implicated as being important mechanisms in the development and maintenance of safe, low crime neighborhoods (e.g., Taylor et al. 1984; Sampson 1988; Sampson et al. 1997; Veysey and Messner 1999; Bellair 2000). The research on the relative importance of local, as well as non-local, social ties is framed within either the systemic model of social disorganization (e.g., Shaw and McKay 1942; Sampson 1986; Sampson and Groves 1989; Bursik and Grasmick 1993) or the more recent conceptual framework of "collective efficacy" (Sampson et al. 1997; Sampson 2004). In either case, these approaches argue that it is the individual-level social bonds among local residents that facilitate the formation of informal social control and the

creation of shared goals and trust that regulate and censure local activities. A general

acceptance of the importance of networks of local social relationships for understanding

rates and patterns of neighborhood crime has prompted researchers to look into the kinds

of social networks operating in communities in an effort to gather information regarding

social ties among local residents, as well as peer associations with delinquent others.[12]

Beyond examining the degree to which individual-level ties influence crime

patterns within a community, researchers are also beginning to explore the importance of

institutional or organizational ties that can bridge communities. In a recent essay, Robert

Sampson (2004:158) argues for reconceptualizing neighborhoods "as nodes in a larger

network of spatial relations" in order to account for the various ties that can link residents

across space. Although Sampson (2004) does not specifically suggest what kinds of local

institutions or organizations one should consider as important to explaining crime, in general

terms he refutes the notion that neighborhoods are analytically independent and argues

that ecological models of crime need to consider the different ways in which the

observable outcomes in one neighborhood are partly the product of social actions and

activities that can stretch beyond local communities (Sampson 2004; Morenoff et al.

2001).

Sampson's (2004) point about unit interdependence reflects the growing trend in

criminology of researchers incorporating spatial effects into their models of crime. And

though the authors of the many studies that have incorporated spatial effects into their

models may not have explicitly constructed their analyses by conceptualizing

"neighborhoods as nodes" in networks of social relations, their use of spatial

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[12] Two notable examples of this are the Project on Human Development in Chicago Neighborhoods (PHDCN) and the Los Angeles Family and Neighborhood Survey (L.A.FANS).

autocorrelation models does just that. These models formalize the way in which communities are geographically linked (Anselin 2002). In fact, spatial regression analysis is simply a particular type of "social influence model" (Marsden and Friedkin 1994; Leenders 2002). Rather than modeling the structural processes by which individuals or organizations are influenced by one another, spatial models formalize the influence that neighboring areas have on a particular phenomenon in a focal area.

Formalizing unit interdependence involves two related challenges. The first lies in identifying the specific social process by which influence occurs. For example, actors in one area may choose to imitate the actions occurring in another area or may be influenced by coming into direct contact with actors from other areas.[13] The second challenge involves determining which units are to be treated as "neighbors" within the influence system. As Leenders (2002) observes, spatial regression models invariably model place-to-place influence through proximity in geographic space, a choice typically justified empirically by the presence of positive spatial autocorrelation, or the tendency of like objects to cluster geographically. However, modeling influence between locations in the absence of strong evidence of positive spatial autocorrelation, or when agents are theorized to transmit influence across longer distances, is more complicated than is allowed for in the standard models based on geographic proximity (Leenders 2002).

Building upon ongoing research into the importance of both social and spatial "position" among gangs embedded within various types of local networks (Radil et al. 2010), we explore the distribution of crime across places using an approach first developed by Tita and Greenbaum (2009). This method accounts for influence through

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[13] Cohen and Tita (1999) argue that processes of imitation and direct influence can be conceptualized as different types of spatial diffusion and provide examples and a discussion of the various mechanisms related to diffusion within the realm of the urban homicide patterns.

imitation and direct contact by simultaneously considering both geographic proximity between places as well as specific social ties that connect places. This approach carefully identifies direct social connections between neighborhoods based on rivalries between urban street gangs that are not geographically proximate, while also preserving the underlying spatial structure of the entire study area.

The remainder of the paper is organized as follows: We begin with a brief summary of the issues identified by Tita and Greenbaum (2009) related to the modeling of social influence, focusing on the specification of the autocorrelation matrix for spatial regression analysis. We then review the findings from the spatial regression analysis of violence paying attention to the interpretation of the coefficient on the spatial term, especially as it pertains to gang violence. After describing the data and carefully considering the geographic unit of analysis, we next specify our different spatial models of violence involving gang members. The results demonstrate that an influence model that allows for influence based on both proximity and specific social relations provides a more robust explanation of the observed spatial distribution of crime than does the standard spatial autocorrelation model. We conclude with a discussion of the findings and their implication for the broader spatial analyses of crime/neighborhood effects literature.

MODELING SOCIAL INFLUENCE ACROSS SPACE

The great majority of research aimed at explaining the spatial distribution of crime, especially violence, has employed an inductive approach in the modeling and

explanation of findings.[14] That is, the structure of influence between communities is modeled geographically using rook's or queen's case contiguity. The implication is that space matters, but that influence is constrained by distance and that nearest neighbors matter most (also known as "Tobler's First Law of Geography" (Tobler 1970)). If the coefficient on the spatial terms is statistically significant, post-hoc explanations centered on contagion (Loftin 1986), exposure (Morenoff et al. 2001; Griffiths and Chavez 2004), gangs (Rosenfeld et al. 1999; Cohen and Tita 1999), and drug markets (Morenoff and Sampson 1997; Cork 1999; Tita and Cohen 2004) have been advanced as the **possible** mechanisms responsible for the spatial clustering of events. Though these studies have been invaluable in empirically demonstrating the existence of unobserved contextual or "neighborhood effects", very little progress has been made in moving these unobserved neighborhood effects into the realm of the observable. To take this next step, Tita and Greenbaum (2009) argue for the adoption of deductive approach in model construction.

The key element in identifying the way that "influence" matters in spatial regression models is the autocorrelation–or spatial weights–matrix, represented by *W*, which captures the structure linking persons, places, or things together. Part of the reason that the mechanisms of influence remain unidentified is related to the way in which the autocorrelation matrix is specified in spatial analysis. Restricting processes of influence to operate only among contiguous neighbors is to ignore processes of influence that are inherently more complex in terms of the spatial extent of interactions (e.g. Sampson 2004). A more deductive approach would consider both the social and the geographic structure of the data and incorporate these complexities into the spatial weights matrix.

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[14] For a detailed review and critique of inductive approaches to modeling influence across space see Tita and Greenbaum (2009).

The construction of $W$ is extremely important in terms of identifying the mechanisms driving influence processes. As Leenders (2002:22) notes: "$W$ is supposed to represent the theory a researcher has about the structure of the influence processes in the network. Since any conclusion drawn on the basis of autocorrelation 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." Put more succinctly, "Change one's theory, change $W$" (Leenders 2002:26.)

A deductive approach built on the understanding that social networks are inherently geographic, existing both within and across localities and connecting communities separated by distance (e.g. Ettlinger and Bosco 2004), offers a promising framework for advancing our understanding of why space matters. This analytic framework allows influence to take place not just between geographically proximate neighbors (as with conventional spatial analysis) but also between locations that are connected by social networks. By carefully considering and allowing for processes that extend beyond (or perhaps preclude) spatially adjacent areas, one can ensure that the spatial weights matrix adequately captures the realities of the mechanisms of influence. Just as Morenoff (2003:997) argues that spatial analysis "…expands the neighborhood-effects paradigm by considering not only the local neighborhood but also the wider *spatial* [emphasis added] context within which that neighborhood is embedded", we argue that careful consideration of the socio-spatial dimensions of social influence will facilitate the inclusion of the "wider *social* context of neighborhoods" into the neighborhood effects literature.

Outside of the examination of crime, there are several examples of innovative efforts that recognize that the processes of influence are not neatly bounded by, or limited to, spatially adjacent 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. He finds that teachers' wages are more alike when contiguity among school districts is based upon socio-economic similarities rather than geographic contiguity. That is, wages in non-adjacent affluent school districts exhibit similar wages when compared to adjacent but non-affluent school districts. 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.

There are fewer examples of studies that "unbound" space within the criminological literature. In addition to the work of Tita and Greenbaum (2009), Mears and Bhati (2006) link adjacent as well as non-adjacent areas to one another if the residents are economically and demographically similar. The stated goal of their research is not to examine "…spatial diffusion processes, wherein violence in one community causes crime in another. Rather, [they] examine whether resource deprivation exerts an influence on violent crime in other communities" (Mears and Bhati 2006:2). On the basis

of "homophily" (Blau and Blau 1982; McPherson et al. 2001), they posit that behaviors in a focal area will be influenced by behaviors in socially similar areas because social similarity increases the probability of interactions among individuals. Mears and Bhati (2006) test this by constructing an autocorrelation matrix based on "similarity" that links socially similar areas together regardless of spatial proximity. This work is an important advance in the modeling of influence by a general contagion process which too often assumes that transmission by social networks occurs through the direct social contact among individuals residing only in spatially adjacent communities (Lofton 1986; Morenoff 2003). Recent work by Papachristos (2007) focuses more on how the structure of gang networks in Chicago influences the pattern of intra- and inter-gang violence. Controlling for spatial adjacency and contested territory, this work demonstrates that proximity between gangs is a strong predictor of retaliatory behavior.

Although as Feld (1981) notes, geographic proximity among individuals can create opportunities for the interactions that constitute social networks, it is not clear that modeling social influence through geographic distance or proximity alone adequately captures the full range of social interactions that researchers believe to be important (see also Reiss and Farrington 1991). The importance of considering ties across geographically distant but socially similar places is further underscored by Sampson and Sharkey (2008) who demonstrate that intra-metropolitan residential mobility patterns are largely confined by either class, race or, in the case of African-Americans, both.

MODELING SPATIAL PATTERNS OF VIOLENCE

Two consistent findings have emerged from the spatial analysis of violence literature. 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. This pattern has been interpreted as evidence of diffusion, or the spread of violence over space and through time. As noted above, inductive approaches have proffered a variety of mechanisms responsible for the diffusion of crime including exposure and the social organization of drug markets. Though these are highlighted elsewhere (see Tita and Greenbaum 2009), the current research focuses specifically on the role of urban street gangs in explaining the spatial distribution of violence (see Decker 1996; Wilkinson and Fagan 1996; Cohen et al. 1998; Cohen and Tita 1999; Rosenfeld et al. 1999; Morenoff et al. 2001; Griffiths and Chavez 2004; Tita and Cohen 2004; Papachristos 2007).

One reason that the presence of an urban street gang has emerged as one of the most common mechanisms implicated as a source of spatial dependence and the spatial distribution of violent crime is that gang-related homicide demonstrates patterns of positive spatial autocorrelation on a more consistent basis than do other types of homicides (Cohen et al 1998; Cohen and Tita 1999; Rosenfeld et al. 1999). This nexus between gangs and the geography of violent crime rests upon two defining features of gangs. First, gangs are geographically oriented in that they have a strong attachment to the territory, or turf, under their direct control. Further, while the total territorial area claimed by a gang may be quite large and vary over time, the "set space" where urban

street gangs come together is a well-defined, sub-neighborhood area that remains consistent over time (Klein 1995; Moore 1985, 1991; Tita et al. 2005). Second, behaviors associated with the control of territory, such as communicating turf boundaries, regulating activities within turf, and defending turf against rivals, are important elements in the diffusion of violence (Sack 1986; Newman 2006; Papachristos 2007). In the process of controlling territorial space, gangs have negative relations (i.e., rivalries) that explicitly tie them to other gangs and to other territories, turfs, and set spaces. The combination of a gang's persistent geographic presence and the territorial behaviors required to defend, maintain, or expand turf help diffuse certain types of violence in urban settings.

While the territorial claims and behaviors of gangs can be understood as an important geographic component to the theory of the spatial distribution of violence, gang turf itself is not an ideal choice as a spatial unit of analysis. Issues surrounding the selection of units of analysis when using data grouped or aggregated to geographical areas, such as border effects or the modifiable areal unit problem, are ever present and, like any area partitioned into discrete units by politically-minded boundaries, gang turf is less than optimal for spatial analysis.[15] Recognizing the importance of the geographic unit of analysis to analytic outcomes when using spatially aggregated socio-economic data, we took steps in data collection to mitigate common issues of unit selection in spatial analysis. Through the use of address-matching in a geographic information system

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[15] Border effects refer to the fact that the often-arbitrary boundaries of study regions may exclude information that affects outcomes within the study region (see Griffith 1983). The modifiable areal unit problem refers to the fact that the results of statistical analysis, such as correlation and regression, can be sensitive to the geographic zoning system used to group data by area (see Gehlke and Behl (1934) or Robinson (1950) for classic examples of MAUP, or Openshaw (1996) for a more contemporary review). While well-established in geography, these issues tend to resurface in other disciplines as spatial analysis becomes more prevalent (for example, see Hipp 2007). For a review of the treatment of these issues in the spatial analysis of crime, see Weisburd et al. (2009).

(GIS), each incident in our crime data is precisely located in space rather than already aggregated to an areal unit. This has the positive effect of freeing subsequent analysis from the use of any particular unit of analysis, allowing the researcher to select a unit that best fits the aims of the research question. We made use of this flexibility in a very specific fashion in this project by overlaying a census block group geography over the gang turf geography. By doing so we were able to rescale the unit of analysis from relatively large areas of gang turf into smaller scale census units. Gang turf claims and violence counts were then assigned to the census units along with aggregate-level socio-economic data. By making use of precisely located crime data, we were able to rescale the unit of analysis, enabling us to examine both compositional and contextual elements of the diffusion of gang violence while helping to mitigate common issues of unit selection in spatial analysis.

Together, the territorial geography of gangs and their social network of rivalries suggest a set of structural properties that researchers have not adequately exploited in terms of understanding the spatial structure of gang violence. As Tita and Greenbaum (2009) point out, this oversight is unfortunate given the existence of social network analyses of gangs which have been used to guide the development and implementation of problem-solving/gun violence reduction strategies (see Kennedy et al. 1997; Tita et al. 2002; McGloin 2005). By combining the gang turf geography with information on the social networks between those gangs, it becomes possible to determine whether rival gangs are located in spatially adjacent areas. If the socio-spatial dynamics of gang enmity are more complex – meaning that they span simple geographic proximity and serve as

mechanisms that can link non-contiguous areas—then the spatial dependence matrix should be specified such that it is able to capture these complexities.

The goal of this research is to better understand the spatial distribution of one type of violence: that which is perpetrated by and/or against gang members. Drawing from existing theories and empirical evidence from the gang literature and the spatial analysis of violence literature, two models are specified. The first model follows the conventional approach and limits the influence of violence in other area on a focal area by restricting the impact among only spatially adjacent areas. The second model considers the socio-spatial dimensions of gangs, which combines spatial data on gang locations with social network data on gang rivalries. In specifying our social process (gang rivalry, retaliation) a priori, we construct a spatial autocorrelation matrix that links observations (census block groups) only when each pair of places contains the gang set space of rival gangs. The central question, then, is this: Does modeling spatial dependence using spatial adjacency best account for the distribution of gang violence, or are additional insights gained by explicitly considering the socio-spatial dimension of gangs and their rivalries? If violence committed by gang members in a neighborhood is influenced by the actions of rival gang members, and if gang rivalries extend beyond geographic neighbors, one might expect the network-based matrix to better explain the observed spatial distribution of crimes in the study area.

Tita and Greenbaum (2009) are careful to note that spatial adjacency may still play an important role in explaining spatial patterns of gang-involved violence. Given that gang members commit more violent crimes than do non-gang members (see Thornberry et al. 2003), a community that is exposed to gang members is likely to exhibit

higher levels of violence. Therefore, any geographic clustering of gang territories should produce spatial autocorrelation in gang violence across the geography. We contend, however, that diffusion driven by the social interactions among gangs involved in ongoing rivalries may *also* (or perhaps, better) explain the observed spatial patterning of violence involving gang members, 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-contiguous areas should inform the specification of one's spatial weights matrix.

RESEARCH DESIGN AND MEASUREMENT

The empirical analysis is conducted using census block group data and geo-coded crime data provided by the Los Angeles Police Department (LAPD) for the Hollenbeck Policing Area (see Figure 4.1.) Hollenbeck encompasses roughly fifteen (15) square miles and has a population of approximately 170,000. Most of the population is Latino (84.5%) and the vast majority are of Mexican descent (82.6%) – half (39.4%) of whom were born in Mexico. The median household income in Hollenbeck is $27,096 and thirty percent of the population lives below the poverty line. Of the total population that is twenty-five years old or older, thirty five percent have less than a high school degree (or equivalent).

Because of physical and geo-political barriers, Hollenbeck is ecologically distinct from neighboring areas. For instance, on the western border the Los Angeles River separates Hollenbeck from downtown Los Angeles. To the south, Hollenbeck borders the city of Vernon, which has a total population of less than 100 and is dominated by

meatpacking and other industrial sites. The unincorporated area of Los Angeles commonly referred to as "East Los Angeles" as well as the city of Pasadena border Hollenbeck to the east/northeast. In addition to the Los Angeles River, numerous freeways dissect Hollenbeck differentiating it from other parts of Los Angeles and creating ecologically distinct neighborhoods within Hollenbeck (e.g., "Boyle Heights", "Lincoln Heights" and "El Sereno"). As demonstrated elsewhere (see Tita et al. 2002; Tita et al. 2003), these borders serve to create a landscape within which the rivalries of the Hollenbeck gangs are wholly contained. As a result, the current research does not suffer from the sort of "boundary effect" inherent in most examples of spatial analysis that are not dealing with a complete social and geographical system.[16]

Hollenbeck has a long and well-studied history of urban street gangs with some of the gangs originating before the Second World War. Joan Moore (1985, 1991) has written extensively on one of the oldest gangs in the neighborhood, White Fence, while other gangs have been the focus of such notable gang researchers as Malcolm Klein (1971) and James Diego Vigil (1988, 2002). The gangs in Hollenbeck are "traditional gangs" (Klein 1995) and have a strong attachment to turf. Violence in Hollenbeck is expressive in nature, with much of it tied to the defense of one's turf (see Tita et al. 2002.) During the research period, between 2000 and 2002, twenty-nine "criminally active" street gangs were identified in Hollenbeck. All other groups such as "tagger crews", "skate punks" and "stoners" were excluded on the basis that, according to local police, they do not participate in violence and they are not territorially defined.

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[16] City-level studies of violence, for instance, often exclude data from spatially contiguous areas located just beyond the focal city's borders not because these areas are unimportant, but rather because the data may not be available. Because none of the rivalries extend to gangs that lie beyond the borders of the research site, there are no non-Hollenbeck rival gangs to be excluded thereby ensuring that the full extent of the social process believed to matter (gang rivalries) is being captured.

*Measures of Gang Turf*

Identifying and mapping the territorial claims of the gangs was made possible by working with detectives and patrol officers assigned to LAPD's Hollenbeck gang unit as well as Los Angeles County probation officers whose caseload was comprised exclusively of Hollenbeck gang members. These gang experts were given detailed, large-scale maps for each of the fifty-six "reporting districts" and then asked to draw the boundaries of each gang. This information was transferred to a geographic information system (GIS) which enabled us to layer a map of census block group boundaries over the gang turf map. We were thus able to disaggregate the turf map and locate the presence or absence of a gang at the census block group level – a level at which evidence suggests is meaningful in the ecological study of gangs (see Tita et al. 2005; Tita and Ridgeway 2007). Of the 120 census block groups included in this study, gangs claimed at least some portion of 103 block groups. In seven instances, two gangs claimed parts of the same block group; sometimes these gangs were rivals, sometimes they were simply "neighbors."

*Measurement of Gang Rivalries*

A list-sort technique was used to identify the rivalries that link the gangs. Each informant was provided with a survey comprised of one page for each gang. At the top of the page, a particular gang was identified and the respondent was asked to "Please Identify All of the Gangs that are an **Enemy** of the <insert gang name>." In addition to the law enforcement experts, several current and former members of gangs also

completed the survey network form. Gang members were accessed through an employment/training center and its founder, a nationally known Jesuit Priest who works with gang members from Hollenbeck and surrounding areas. Though only members from six of the 29 gangs completed surveys, there was perfect agreement across the gang members' and law enforcement experts' surveys regarding the enmity connections between gangs. A sociogram depicting the structure of the gang rivalries is provided in Figure 4.2

*Measures of Gang Violence*

The dependent variable includes all violent crimes committed by or against gang members in the Hollenbeck Policing Area between May of 2000 through December of 2002.[17] Therefore, the violence is "gang related" and includes both "gang motivated" violence (e.g., protection of turf from an incursion by rival members) as well as all other violence involving a gang member. The total number of crimes included in the study is 1,223, or an average of 10.2 violent gang crimes per block group (n=120) over the thirty-month period. The crime types included in the file are all aggravated assaults, simple assaults, assault with a deadly weapon, attempted homicides, homicides, robberies, kidnappings, and firing a gun into an inhabited dwelling/vehicle. The spatial distribution of these crimes is presented in Figure 4.3. Rape and instances of domestic violence are excluded from this analysis because the data were unavailable. Sexual and/or domestic

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[17] Research has demonstrated that in this area of Los Angeles, gang involved violence accounts for 75% of all lethal violence (see Tita et al. 2003). Additionally, the current analysis was performed on all violent crimes regardless of gang involvement. Not surprisingly in light of the gang dominance in the commission of violent acts, there were no differences. These analyses are available from the authors upon request.

violence is also less likely to be influenced by either exposure or diffusion processes operating at the neighborhood level.

*Ecological Measures*

Included in the models is a set of commonly used indicators of neighborhood structural composition associated with high levels of homicide (Land et al. 1990; Krivo and Peterson 1996). Specifically, the following 2000 census variables are included in the analysis: the percentage of residents that are of Hispanic origin, the median household income, the percentage of households that are headed by females, the percentage of residents who rent, the percentage of adults over the age of twenty-five with less than a high school (or GED) degree, the percentage of residents who moved into the community in the last five years, the percent of housing units that are vacant, the percentage of residents between the crime prone ages of fourteen to twenty-four years of age, and population density. A dichotomous variable to distinguish among high poverty (between twenty and forty percent of the population in poverty) and extreme poverty (at least forty percent of the population living in poverty) neighborhoods from low poverty neighborhoods was also constructed (see Krivo and Peterson 1996). Finally, the model controls for the area (square miles) of the census block group. Descriptive statistics for the independent variables, along with the dependent variable, are presented in Table 4.1.

*Measurement of the Weights Matrix*

The geographically based spatial weights matrix ($W_g$) is based on rook's case first-order contiguity and was constructed using the GeoDa software (version 0.95i) for spatial analysis (Anselin et al. 2006).[18] We settled on this specification after specifying several different spatial configurations and then examining the amount of spatial autocorrelation in the number of gang crimes per block group. The most common statistic used to determine the overall pattern of spatial autocorrelation is Moran's $I$, which is very similar to a simple correlation coefficient. The formula is given by:

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

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.) Both rook's case (neighbors defined by shared border lengths) and queen's case (neighbors defined by a shared border point) configurations were tested for first-order neighbors (those that are immediately contiguous to the focal unit), second-order neighbors (those that are immediately contiguous to the focal unit's first-order neighbors), and first- and second-order neighbors combined. The Moran's $I$ results for these different configurations are presented in Table 4.2.

Based on these results, it is clear that the spatial autocorrelation of gang crime diminishes quickly across space when using census block group geography. Crime counts show weak but statistically significant measures of positive spatial autocorrelation for rook's case first-order neighbors ($I = 0.0907$ with a significance level of 0.047), but when

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[18] As discussed previously, we theorize that the territoriality of gangs is at the heart of rivalry relations between gangs. However, we do not limit the $Wg$ matrix to include only units already claimed by neighboring gangs. We see areas that were unclaimed at the time of the study as something that gangs may compete over as well.

second-order neighbors are considered, the results show weakly negative spatial autocorrelation. Based on these results, rook's case first-order contiguous neighbors form the $W_g$. The weights matrix can also be depicted as a network drawing where the nodes are the block groups and an edge between block groups means that they are adjacent (see Figure 4.4).

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 space (i.e., turf or "set space"). This matrix, $W_n$, was constructed by first creating a location-by-gang matrix with dimensions of m x n (120 block groups x 29 gangs). The dark colored nodes in the network diagram in Figure 4.5 represent the gangs while the lighter shaded nodes presents each of the census block groups. This matrix was then multiplied by the n x n (29 x 29) enmity network followed by the transpose of the location-by-gang matrix (29 x 120). After executing the matrix algebra one is left with a two-mode, m x m (120 x 120) matrix that identifies census block groups that are "enemies" of one another. That is, a non-zero value in a cell of $W_n$ indicates that the pair of block groups is linked because they both contain the turf of rival gangs.

Repeating the Moran's $I$ analysis but using the network derived weights matrix, $W_n$, $I = 0.124$ and is statistically significant at the 0.015 level. While Moran's $I$ tests for both $W_g$ and $W_n$ demonstrate positive spatial autocorrelation, the test statistic is larger when the network-based $W$ is used. However, it is incorrect to evaluate the two approaches based upon the magnitude of Moran's $I$ without also examining the significance levels. Because the significance level is greater for $W_n$, the level of spatial

autocorrelation is more consistent with the socio-spatial dimensions of gang rivalries rather than the simple contiguity-based measure of influence.

Figure 4.6 provides a visualization of the network-derived weights matrix ($W_n$). Yet this picture is deceptive because many of the nodes (census block groups) are, in network terms, structurally equivalent.[19] That is, every block group that contains the turf of gang "A" is tied in exactly the same way with every other block group that contains the turf of "A's" rival. This is demonstrated graphically in Figure 4.7 where the same node, #11, identified in the circle in Figure 4.6, has been "spread out" to show that there were actually two other nodes (#5 and #7) that are also tied to exactly the same set of nodes. Thus, the network matrix is no longer a fully connected binary matrix where every unit has at least one neighbor, but instead one where some block groups have no neighbors while others have multiple ties to the same block group (as in the case where multiple gangs share the same block group and also share a common enemy.)

MODELS OF GANG VIOLENCE

To model the impact of both geographical space and social space on the spatial distribution of gang involved violence, we use a spatial dependence model, also commonly referred to as a "spatial lag" model. While the spatial error model is appropriate when one is concerned about unmeasured endogenous effects among spatially proximate areas, given that we are interested in exploring two specific

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[19] The two most common approaches to equivalence in network analysis are structural equivalence and regular equivalence. The most important difference between the two is that structural equivalence requires that equivalent actors have the same connection to the same neighbors while regular equivalent actors have the same or similar patterns to potentially different neighbors (see Doreian et al. 2005).

contextual processes, the spatial lag model represents the appropriate choice.[20] The

general form of autocorrelation models, be they spatial or network, is given by,

$$Y = \rho Wy + X\beta + \varepsilon,$$

Where $\rho$ is a scalar representing the spatial autoregressive parameter, $W$ is the

weights matrix that formalizes the relationship among geographic units, X is the matrix

of exogenous independent variables, $\beta$ is a vector of regression coefficients, and $\varepsilon$ is an

error term that is assumed to be normally distributed; so $\varepsilon \sim N(0, \sigma^2 I)$.

Standard OLS regression is inappropriate because $Wy$ is endogenous. Therefore,

both MLE or two-stage least squares have been demonstrated to provide the best

estimates of the parameters of interest (Anselin 1988; Land and Deane 1992).  We adopt

what has become known as the "Anselin Alternative Method," which entails a two-stage

estimation process where the spatially lagged dependent variable ($Wy$) is estimated using

an instrumental variable (IV). As suggested by Anselin (personal communication,

November 12th, 2004), and has been done in other spatial models employing IVs, the

spatial lag of crime is instrumented using the "crime potential" which is simply the

spatial lag of the *predicted values* of crime (Kubrin and Weitzer 2003; Morenoff and

Sampson 2004; Tita and Greenbaum 2009). Because the IV is based upon predicted

values, there is a high likelihood that the error terms in the second stage of estimation

will be correlated. Therefore, we follow the lead of Meyer et al. (2002) and employ the

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[20] The choice of model should always be predicated on a particular theoretical argument. However, in
exploratory work, model choice is often determined empirically based upon the results of diagnostic tests aimed
at distinguishing which model (error or lag) best fits one's data.  Anselin suggests that one first consider the
Lagrange multiplier test (LM). If this test is failed, then the structure of the data suggests a spatial lag process is
appropriate over the alternative choice of a spatial autoregressive error model (Anselin 2002). Though the
specification tests are meant for continuous variables, several transformations (logging, creating rates) of the
current dependent variable (crime count) demonstrated support for the lag model over the spatial error model.

Murphy and Topel (1985) correction to the standard errors in the second stage of estimation. The estimation of this model was completed using Stata 8.2 SE (StataCorp 2005) and the "QVF" routine that fits generalized linear models using IRLS (maximum quasi-likelihood). The model is estimated by specifying the negative binomial as the underlying distribution of the dependent variable and the link function is set equal to the log function.

We estimate four models. First, in order to obtain the predicted values for the number of crimes in each block group, gang violence is modeled only as a function of the community-level (block group) structural variables as follows:

$$Y = \beta_0 + \beta_1 \%\text{Hispanic} + \beta_2 \text{MedHHInc} + \beta_3 \%\text{FemHH} + \beta_4 \%\text{Renters} + \beta_5 \%\text{NewRes} + \beta_6 \%\text{VacantProp} + \beta_7 \text{ExtremePov} + \beta_8 \text{HighPov} + \beta_9 \text{PopDensity} + \beta_{10} \text{NoHS} + \beta_{11} \%\text{CrimeAge} + \beta_{12} \text{Area} + \varepsilon \qquad \text{(Eq1.)}$$

To test whether gang involved violence in a focal neighborhood is influenced by levels of such violence among contiguous units, we next use the predicted values of crime ($\hat{y}$) multiplied by the spatial weights matrix, $W_g$, as an IV (for the regular spatial lag of crime counts, $W_g y$) in the second-stage of estimation.

$$Y = \beta_0 + \rho W_G \hat{y} + \beta_1 \%\text{Hispanic} + \beta_2 \text{MedHHInc} + \beta_3 \%\text{FemHH} + \beta_4 \%\text{Renters} + \beta_5 \%\text{NewRes} + \beta_6 \%\text{VacantProp} + \beta_7 \text{ExtremePov} + \beta_8 \text{HighPov} + \beta_9 \text{PopDensity} + \beta_{10} \text{NoHS} + \beta_{11} \%\text{CrimeAge} + \beta_{12} \text{Area} + \varepsilon \qquad \text{(Eq2.)}$$

The third model examines the socio-spatial dynamics of gang rivalries on observed patterns of violence involving gang members. This model is identical to Equation 2 except the IV is a function of the weights matrix based upon the network ties linking geography ($W_n$) and the predicted values of *y*.

$$Y = \beta_0 + \rho W_n \hat{y} + \beta_1 \%\text{Hispanic} + \beta_2 \text{MedHHInc} + \beta_3 \%\text{FemHH} + \beta_4 \%\text{Renters} + \beta_5 \%\text{NewRes} + \beta_6 \%\text{VacantProp} + \beta_7 \text{ExtremePov} + \beta_8 \text{HighPov} + \beta_9 \text{PopDensity} + \beta_{10} \text{NoHS} + \beta_{11} \%\text{CrimeAge} + \beta_{12} \text{Area} + \varepsilon \qquad (\text{Eq3.})$$

The final model includes both the spatially lagged and socially lagged predicted values as the IV for their respective spatial lags and is defined as:

$$Y = \beta_0 + \rho W_g \hat{y} + \rho W_n \hat{y} + \beta_1 \%\text{Hispanic} + \beta_2 \text{MedHHInc} + \beta_3 \%\text{FemHH} + \beta_4 \%\text{Renters} + \beta_5 \%\text{NewRes} + \beta_6 \%\text{VacantProp} + \beta_7 \text{ExtremePov} + \beta_8 \text{HighPov} + \beta_9 \text{PopDensity} + \beta_{10} \text{NoHS} + \beta_{11} \%\text{CrimeAge} + \beta_{12} \text{Area} + \varepsilon \qquad (\text{Eq4.})$$

RESULTS

The results of the regressions are presented in Table 4.3. In the non-spatial model used to obtain the predicted values to be used as IV's, poverty and female-headed household are found to be statistically significant predictors of gang crime. Similarly, block groups with a higher proportion of Hispanics and those with greater population density also experience higher levels of gang violence. We included the percentage of Hispanic residents to control for the geography of project housing in the study area. While the overall demographic composition of the study area is largely Hispanic, there is considerable variation in the percentage of Hispanic residents at the scale of block groups and the units with the highest percentages of Hispanic residents largely track with the presence of housing projects. 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 Petersen 1996; Morenoff et al. 2001; Mears and Bhati 2006). Similarly, population density, an indicator of informal local social control, is positively associated with crime and violence. Counter to expectations, areas with a higher

percentage of the population renting experience lower levels of gang crime. We also find that larger census block groups contain more gang crime.

When the spatially lagged crime variable is added to the model, poverty measures (+), the percent Hispanic (+), and the percent renting (-) continue to be statistically significant. The spatial lag, however, sits right at the cusp of statistical significance (t=0.068). Although this variable is often found to be statistically significant in the analysis of aggregate levels of lethal and non-lethal violence (Morenoff and Sampson 1997; Rosenfeld et al.1990; Baller et al. 2001; Morenoff and Sampson 2004), this does not appear to be the case when the focus is specifically on gang violence. This finding is consistent with the results achieved by Mears and Bhati (2006), but contradicts the de facto explanations offered in most studies of the spatial distribution of all types of homicide that often evoke "gangs" as one of the chief contributors to the positive spatial dependence among events.

By replacing the lagged crime variable created using the contiguity matrix ($W_g$) with the lagged crime variable produced using the network based measure ($W_n$), we find that poverty is significant. Consistent with the results from the first two models, a larger concentration of Hispanic residents is also significantly associated with higher levels of gang violence. Once again we find that larger areas are more likely to contain a greater number of incidents. Most importantly, the network based spatial lag variable is positive and significant. This suggests that gang rivalries do indeed impact the observed spatial distribution of gang violence, but that such linkages matter in ways that extends well beyond simple spatial contiguity.

The final model contains both the spatial lag and the network lag of crime. The results are consistent with model 3. The network lag of crime remains statistically significant but the spatial lag does not. However, it is known that some rivalries among some gangs occur between gangs in neighboring tracts; therefore, there is some overlap between the two weights matrices. This is supported empirically by the positive and significant correlation between the spatially lagged values of crime and the network-based lagged values of crime (correlation coefficient = 0.35, t=0.001). Borrowing again from the field of social networks, we explored this issue by employing a method used to evaluate the correlation between the matrices. We used a quadratic assignment procedure correlation to determine the level of association between the $W_g$ and $W_n$ matrices (see Krackhardt 1988; Dekker et al. 2007). Using randomization techniques, the matrices are positively correlated (r = 0.076, p < 0.001) which may mean that the combined matrix is somewhat overspecified (see Florax and Rey 1995). However, in keeping with the advice of Getis and Aldstadt (2004:91), we feel that the best approach is by using a combined matrix that is grounded in the empirical reality of a two-part spatial structure, one that captures distance effects ($W_g$) and one that captures effects that are relatively invariant to distance at the scale of this study ($W_n$).

The above approach is in fundamentally in concert with the main theme of this paper, which is allowing theory to guide spatial modeling. However, we also addressed the potential for multicollinearity between the $W_g$ and $W_n$ matrices to dampen the impact of the purely spatial lag by performing a "J-test." A full treatment of the J-test can be found in Leenders (2002). In summary, the test statistic provides a method by which one can set up competing hypotheses; jointly estimate alternative autocorrelation models (see

Equation 5 below); and then determine whether the estimated parameter on the

alternative autocorrelation term (Ha) is significantly different from zero (Ho). If so, then

the null can be rejected in favor of the alternative specification of the weights matrix, $W$.

For this study, the initial test is set up as follows:

Ho: $y = \rho_0 W_g y + X_0 \beta_0 + \varepsilon_0$

Ha: $y = \rho_1 W_n y + X_1 \beta_1 + \varepsilon_1$

Consistent with the notation above, $W_g$ is the contiguity-based lag of the

dependent variable, $y$, and $W_n$ is the network-based lag of $y$. In this case, the vectors of

explanatory variables, $X_0$ and $X_1$, are identical, though this is not a necessary condition.

The joint estimation is computed using the following equation:

$$y = (1 - \alpha)(\hat{\rho}_0 W_0 y + X_0 \hat{\beta}_0) + \alpha(\hat{\rho}_1 W_1 y + X_1 \hat{\beta}_1) + v \qquad \text{(Eq 5)}$$

If the true value of alpha is equal to zero, then one cannot reject the null hypothesis. As

Leenders notes (2002:39), $\hat{\rho}_1 W_1 y + X_1 \hat{\beta}$ is independent of $v$ and therefore one can

simply test whether alpha equals zero by using a standard t-test. In other words, the J-test

involves testing whether the coefficients on the lagged predicted values of $y$ ($W_g \hat{y}, W_n \hat{y}$),

which were used as the instrumental variables in the models above[21], are statistically

significant predictors of the observed distribution of crime (see Equation 6)

$$y = W_i \hat{y} + \varepsilon, \qquad \text{(Eq 6)}$$

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[21] Note that by using the spatially lags of the predicted values, we used a variant of the J-test as originally presented in Leenders (2002). Leenders now believes the original specification is incorrect, and favors this alternative specification, which he refers to as a "spatially corrected y-hat," (personal communication, July 22nd, 2007.). The J-test was implemented using both specifications with no substantive differences. Though there were some differences in the size of the standard errors, the coefficients did not change. Both confirm the finding that the network-based specification of $W$ better explains the observed spatial pattern of violence involving gang members.

where $W_i$ is either the network-based measure of dependence or the contiguity-based measure of dependence. The researcher is free to specify either autocorrelation matrix under the null hypothesis. To insure that the conclusion one reaches is not simply a byproduct of which matrix is chosen as the null, the specifications of the null and alternative are reversed and Equation 6 is estimated a second time.

The null hypothesis is initially specified under the condition in which the predicted spatially lagged variables were constructed using the spatial contiguity matrix ($W_g$). As reported in Table 4.4, the coefficient on the lagged spatial term is not statistically significant (t=0.151.) Therefore, one cannot reject the null hypothesis that the true value of alpha = 0. It does not follow, however, that the geographically based weights matrix ($W_g$) provides a better measure of dependence than does the network-based measure ($W_n$). To test which specification of the weights matrix better predicts the outcome, the null hypothesis is then specified using the lagged network term. Under this specification the coefficient on the lagged predicted values is found to be statistically significant at the t=0.001 level. It is now possible to reject the null hypothesis that alpha is equal to zero in favor of the alternative. Therefore, we rejected the hypothesis that $W_g$ is correct in favor of the alternative that $W_n$ is the more appropriate specification of the autocorrelation/dependence matrix.

CONCLUSIONS

A growing number of studies in the social sciences have adopted spatial regression in an effort to model and understand neighborhood effects (see Sampson et al.

2002; Ward and Gleditsch 2008).[22] In criminology, these efforts have used spatially lagged variables as proxies for various social phenomena thought to be responsible for the consistent finding that spatial clustering of crime events remains even after controlling for place-to-place variations in compositional effects such as race, ethnicity and poverty. While we see these efforts as a positive first step toward a "spatially integrated" criminology (see Goodchild et al. 2004), the way in which space is incorporated requires careful consideration. Specifications of the spatial weights matrix that rely on spatial contiguity to define the spatial reach of the various social processes posited to be responsible for clustering forces researchers to assume that all such processes decay rapidly over geographic distance, and therefore matter only among spatially contiguous neighbors. Furthermore, even when multiple social processes are considered, the conventional modeling approach is to specify a single spatial weights matrix rather than specify different kinds of connections between places for different social processes. In addition to making it impossible to parse the impact of one process from that of another, this is an atheoretical approach to understanding why and how space matters (Leenders 2002).

Building on these perspectives, this research focuses on the particular outcome of violence involving gang members and demonstrates that "space" continues to matter as the compositional characteristics of places cannot adequately account for the overall geographic patterns of violence. And while our findings also verify that researchers have

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[22] We are sensitive to arguments that quantitative modeling is not the only way to approach issues of crime in place specific settings. Although the methods demonstrated in this article are capable of standing alone, they seem particularly valuable when used in concert with other ways of knowing. As noted in the discussion of specific findings about the spaces of gang rivalry in Hollenbeck, the analytic methods used in this article answer some questions and suggest others, and are not offered as an absolute substitute for granular, situated, and ethnographic knowledge.

been correct in suggesting that gang rivalries are an important mechanism in the spatial distribution of gang-related violence, our findings show that the spatial reach of these rivalries extends well beyond simple contiguity even when considering different units of analysis, such as those defined by gang territorial boundaries, or at the smaller scale of census units. That is, gang rivalries play an important role in influencing levels of violence across the study area but the geographic scope of these rivalries is not limited to adjacent neighbors. By carefully considering the socio-spatial dimensions of gangs in terms of their territorial claims and the rivalry networks that connect them, it is possible to create a spatial weights matrix that explicitly captures the geographic dimensions of the patterns of social influence among the gangs. We find that the violence committed by, and against, gang members in a socially and geographically distinct area of Los Angeles is largely a function of a *social* process that spans the local geography in such a way that violence in non-contiguous areas impacts levels of violence in a focal neighborhood.

Before concluding with a brief discussion of the importance of our findings to crime prevention policies, we wish to draw attention to three interrelated arguments about why the lessons learned are far reaching for all types of spatial regression analysis in the study of crime. First, given that the presence of spatial or neighborhood effects is well-established in crime research, a deductive approach to the understanding of neighborhood effects should be preferred over inductive, post-hoc explanations. By positing a particular social influence process (rivalry) for a particular type of phenomenon (gang violence), we are able to allow our theory of place-to-place influence to guide the construction of the spatial weights matrix. This is a meaningful step forward given Leenders' (2002) concern with the lack of careful consideration of the underlying social processes of influence

exhibited by researchers in their construction of weights matrices. An important corollary to a deductive approach is that one must carefully match socio-spatial processes to the specific type of event being studied. For instance, focusing on drug violence might lead one to specify a weights matrix that captures the important geographical information pertaining to the location of the markets as well as the spatial dimensions of the actors involved within the markets. A one-size-fits-all approach to the modeling of spatial effects of different types of crime is insufficient in a deductive framework, and as Tita and Greenbaum (2009) noted in their initial work, adapting Leenders' (2002:26) "change one's theory, change $W$" statement to the current discussion, one is reminded to "change one's *crime*, change $W$."

Second, and clearly related to the first, is the need to look beyond measures of simple contiguity when incorporating spatial effects into models of crime without necessarily disregarding the underlying spatial structure of a given study area. This argument takes on added relevance in light of the developing arguments about the importance of micro-scale units of analysis in criminology (see Weisburd et al. 2009). Reducing the areal extent of the unit of analysis may also reduce the potential for place-to-place influence or interaction when modeled through contiguity alone. However, we are not arguing for throwing out the baby of contiguity with the bathwater. In fact, contiguity can be an important way to incorporate the overall spatial structure of a study area, an meaningful goal in the face of likely spillover or other unmeasurable spatial effects (which may increase as the areal scale of the unit of analysis decreases) (Anselin 1988). Further, contiguity is theoretically justified when exposure is meant to capture social influence processes wherein local offenders transgress into neighboring areas to

commit their crime, or when they influence residents in neighboring areas to carry/use guns. Our approach to specifying a spatial weights where place-to-place connections can be defined on both the presence of social network ties and on geographic contiguity demonstrates that researchers are not faced with an either/or choice and contiguity can be included with other more-theoretically informed models of place-to-place influence.

Third, conducting an ecological analysis of gang violence presents an interesting problem with respect to choosing the correct spatial unit of analysis. On the one hand, researchers have argued that the that the "set space" – the activity space of the gang – can often only occupy an area as small as a block face, street corner, or perhaps the front yard of a permissive parent (Whyte 1943; Moore 1991; Klein 1995; Tita et al. 2005). On the other hand, the territory or "turf" that an individual gang often claims as their domain may encompass entire neighborhoods. In the Hollenbeck Policing Area there are clearly examples of both types of gangs. Revisiting Figure 4.5, we see that certain gangs actually claim different parts of *the same* relatively small census block groups used in this analysis. For instance, at the bottom center of the figure we see that Gang 4 and Gang 2 share block group 72 and that Gangs 6 and 22 share geography 8. Gang 22 is a particularly interesting case as it also claims two of the same block groups as does Gang 12. This suggests, perhaps, that block groups might be too coarsely grained to adequately capture the activity space of a particular gang or gangs. Alternatively, the gang prominently displayed in the middle of the figure (Gang 28) is known to occupy space in fourteen different geographies, sharing none with any other gangs. In this case, one might argue that block groups are in fact too fine grained a unit of analysis and that these block groups should be collapsed into a single unit of observation and tied to Gang 28.

The above clearly illustrates that researchers interested in understanding the nexus between the socio-spatial dimensions of urban street gangs and the spatial distribution of violence must think carefully about the unit of analysis. However, we also recognize that crime is not simply a function of the socio-spatial dimensions of gangs. Therefore, we also wanted to be sure to include measures that we believe are theoretically important to explaining crime (e.g., poverty, residential stability, race/ethnicity, etc.). We chose census block groups as our unit of analysis for much the same reason that most researchers who model the ecology of crime do: Census block groups are the smallest unit of geography for which meaningful data are available. One should also not forget the advice of Hipp (2007) who reminds us that ultimately there is no "best" unit of analysis and that the choice of spatial unit of analysis should be driven by empirical and theoretical evidence which supports the social process matching the spatial scale of analysis. Similar to Leenders' (2002:26) advice that "change one's theory, change $W$", Hipp might say "change one's social process, change the unit of analysis."

Lastly, the value of understanding the socio-spatial dimensions of gang rivalries has important implications for understanding and evaluating geographically targeted policies. Mears and Bhati (2006) echo this by pointing to the spatial displacement literature and stating that in addition to considering spatial displacement "there is a greater need to couple such analysis with theoretically informed assessments about ripple effects that may occur along geographic and social dimensions" (Mears and Bhati 2006:25). In fact, the evaluation of a gun violence reduction strategy employed in Los Angeles did just that. The intervention was aimed at reducing the commission of gun violence by gang members by allocating additional resources (primarily law enforcement,

but also social services) in the neighborhoods occupied by specific gangs (Tita et al. 2003). In their evaluation of the effort, the authors demonstrate that in addition to displacing the benefits of the intervention spatially, the intervention also had the effect of quelling gun violence among the rivals of the gangs that were targeted for focused enforcement.

The existence of positive spatial autocorrelation is well supported within the extant crime and place literature. The value of inductive approaches in terms of positing various theories and mechanisms responsible for observable patterns of crime cannot be over-stated. However, after nearly two decades of spatial regression models of crime, it is time to "un-bound" space and to consider the geographic complexities of mechanisms of influence such as exposure and/or diffusion. That is, we need spatial models that adequately capture patterns of social interaction to determine the true geographic dimensions of influence. The current research has demonstrated the value of employing such an approach. We were able to posit a mechanism (gang rivalry) and then use empirical observations to construct an autocorrelation matrix that adequately captured this mechanism that is so often posited as a major contributor to the clustering of crime in space. But with the exception of urban street gangs, we know little about the geography of influence for other types of crimes. It is our hope that others to adopt a deductive approach to explore other types of violence and crime.

Table 4.1: Descriptive Statistics of Variables

| Variable Names (n=120) | Minimum/ Maximum | Mean (Standard Deviation) |
|---|---|---|
| Independent Variables: | | |
| Population Density (per sq. mile) | 865 15471 | 6283 (3928) |
| Area (sq. miles) | 0.059 1.822 | 0.296 (0.238) |
| Median Household Income | 11,573 70,625 | 28,233 (9,656) |
| %Female Headed Households | 0.0 57.14 | 14.80 (9.67) |
| %Rent | 21.30 100.00 | 66.13 (18.59) |
| %Vacant | 0.0 18.18 | 5.17 (3.32) |
| %Living in Same House | 0.0 87.60 | 53.77 (14.65) |
| %Less than High School (25 yrs or older) | 0 86.67 | 60.17 (17.45) |
| %Crime Age (14-24 Years Olds) | 32.75 50.45 | 40.66 (2.80) |
| High Poverty | 0 1 | 51.93 (50.15) |
| Extreme Poverty | 0 1 | 20.15 (40.27) |
| % Hispanic | 22.38 100.00 | 83.57 (18.57) |
| Dependent Variable | | |
| Number of Crimes | 3 44 | 10.19 (9.18) |

Table 4.2: Moran's *I* test results for spatial autocorrelation of the number of violent gang crimes

| | Rook's case contiguity | Queen's case contiguity |
|---|---|---|
| **First-order contiguity** | 0.0907* | 0.0821 |
| **Second-order contiguity only** | −0.0865* | −0.0356 |
| **First- and second-order contiguity combined** | −0.0095 | −0.0367 |

**\* significant at 5%**

Table 4.3: Regression Results (Dependent Variable – Number of Violent Gang Crimes)

| | (1) Predicting Crime | (2) Contiguity-based Lag | (3) Network-based Lag | (4) Both Lags |
|---|---|---|---|---|
| Population Density | 0.047 (3.27)** | 0.036 (0.98) | 0.040 (1.19) | 0.031 (0.88) |
| Area (square miles) | 0.796 (2.60)** | 0.822 (1.43) | 1.240 (2.06)* | 1.233 (2.06)* |
| Median Household Income | 0.072 (0.89) | 0.092 (0.54) | 0.132 (0.79) | 0.147 (0.76) |
| %Female Headed Households | 2.137 (3.55)** | 1.544 (1.16) | 1.749 (1.36) | 1.486 (1.12) |
| %Rent | −0.015 (4.02)** | −0.017 (2.09)* | −0.012 (1.51) | −0.013 (1.58) |
| %Vacant | −0.019 (0.88) | −0.044 (0.79) | −0.028 (0.59) | −0.038 (0.72) |
| %Living in Same House | 0.001 (0.34) | −0.005 (0.52) | −0.009 (0.94) | −0.012 (1.22) |
| %Less than High School | 0.010 (1.39) | −0.012 (0.49) | −0.000 (0.01) | −0.011 (0.47) |
| %Crime Age (14-24 Years Olds) | 0.003 (0.16) | 0.048 (0.75) | −0.015 (0.34) | 0.011 (0.18) |
| Extreme Poverty | 0.902 (4.30)** | 0.910 (2.05)* | 0.971 (2.24)* | 0.934 (2.10)* |
| High Poverty | 0.765 (4.88)** | 0.876 (2.60)** | 0.845 (2.67)** | 0.869 (2.61)** |
| % Hispanic | 0.027 (7.79)** | 0.022 (2.53)* | 0.023 (3.50)** | 0.022 (2.82)** |
| Spatial Lag of Crime | | 0.186 (1.82) | | 0.093 (0.87) |
| Network Lag of Crime | | | 0.085 (2.54)* | 0.083 (2.43)* |
| Constant | −0.673 (0.68) | −3.818 (1.00) | −0.480 (0.21) | −2.332 (0.64) |

Observations (n=120)

Absolute value of z-statistics in parentheses

**\* significant at 5%; \*\* significant at 1%**

Table 4.4: J-Test Results

| | Coefficient | Std. Error | z | P>\|z\| |
|---|---|---|---|---|
| **Contiguity-based lag** | 0.059 | 0.040 | 1.44 | 0.151 |
| **Network-based lag** | 0.055 | 0.016 | 3.37 | 0.001 |

Figure 4.1: Map of study site



Location of Hollenbeck

* South Pasadena

* East Los Angeles
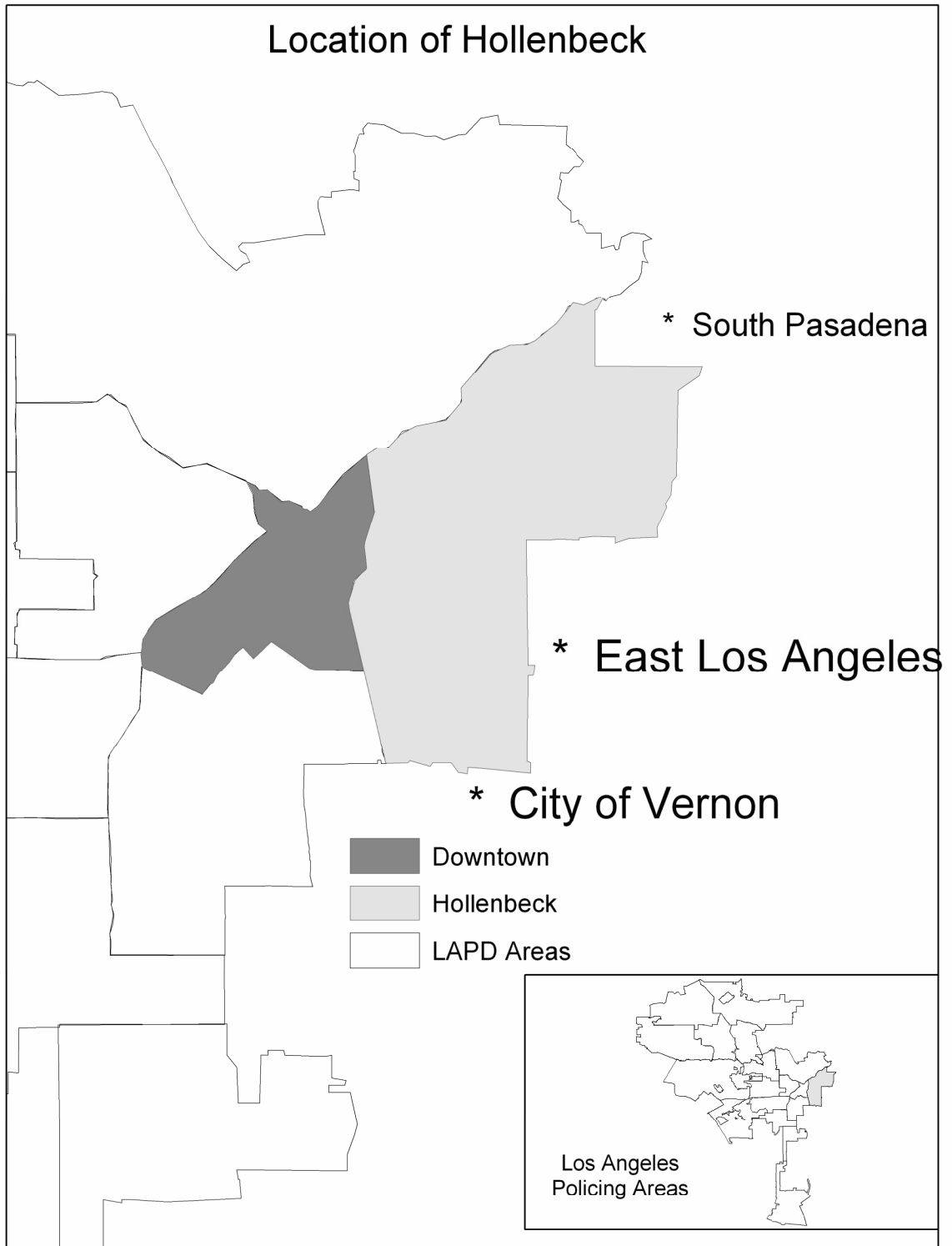
* City of Vernon

Downtown
Hollenbeck
LAPD Areas

Los Angeles
Policing Areas

Figure 4.2: Sociogram of gang rivalries
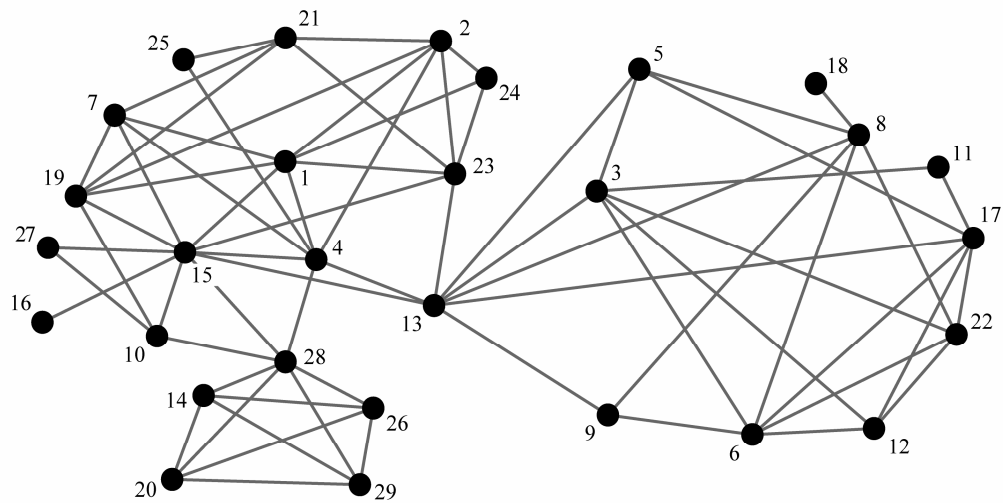
Figure 4.3: Spatial distribution of violent gang crime



Figure 3: Spatial Distribution of Violent Gang Crime

- Crimes (n=1,223)
- Block Groups (n=120)
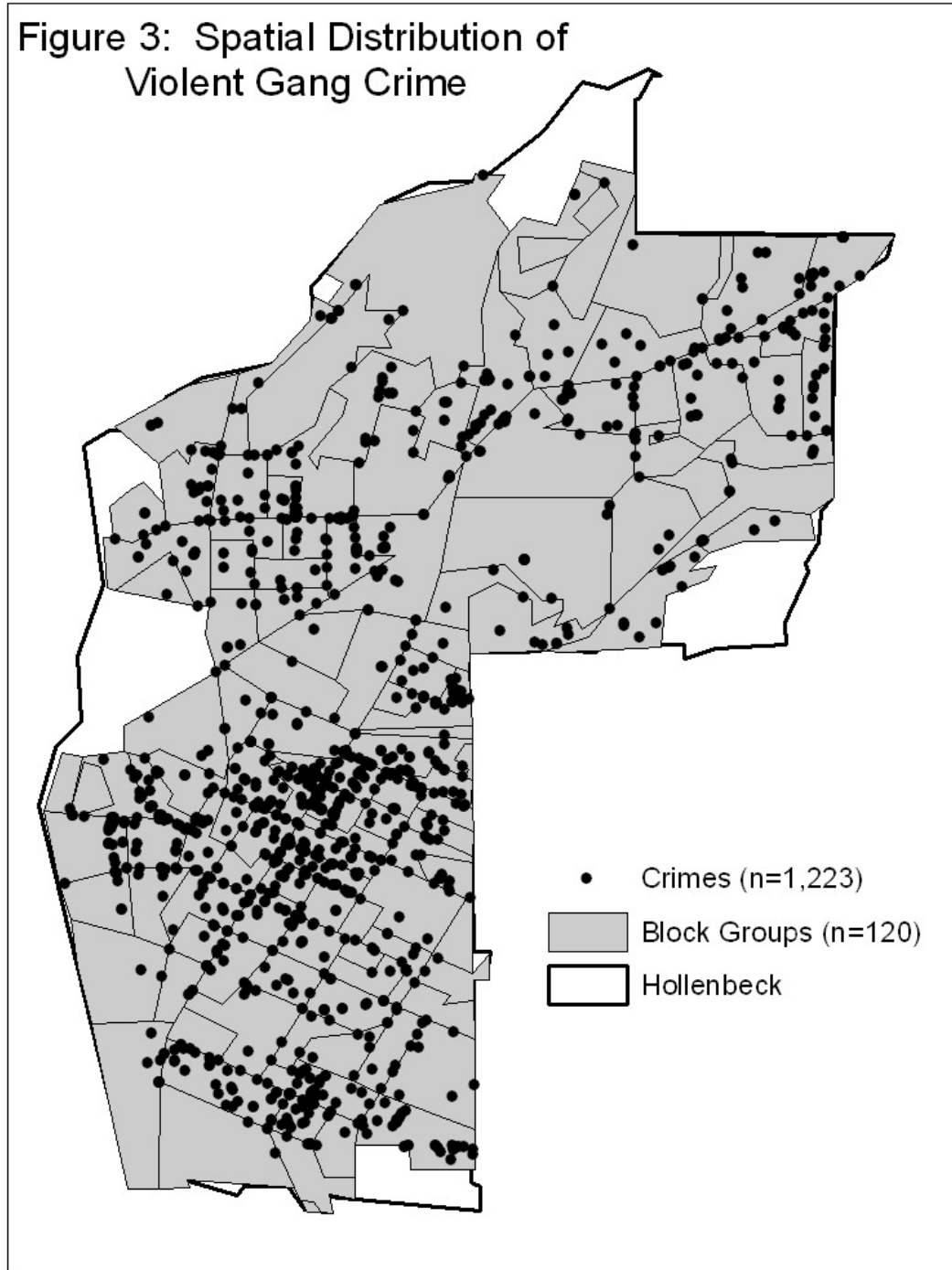- Hollenbeck

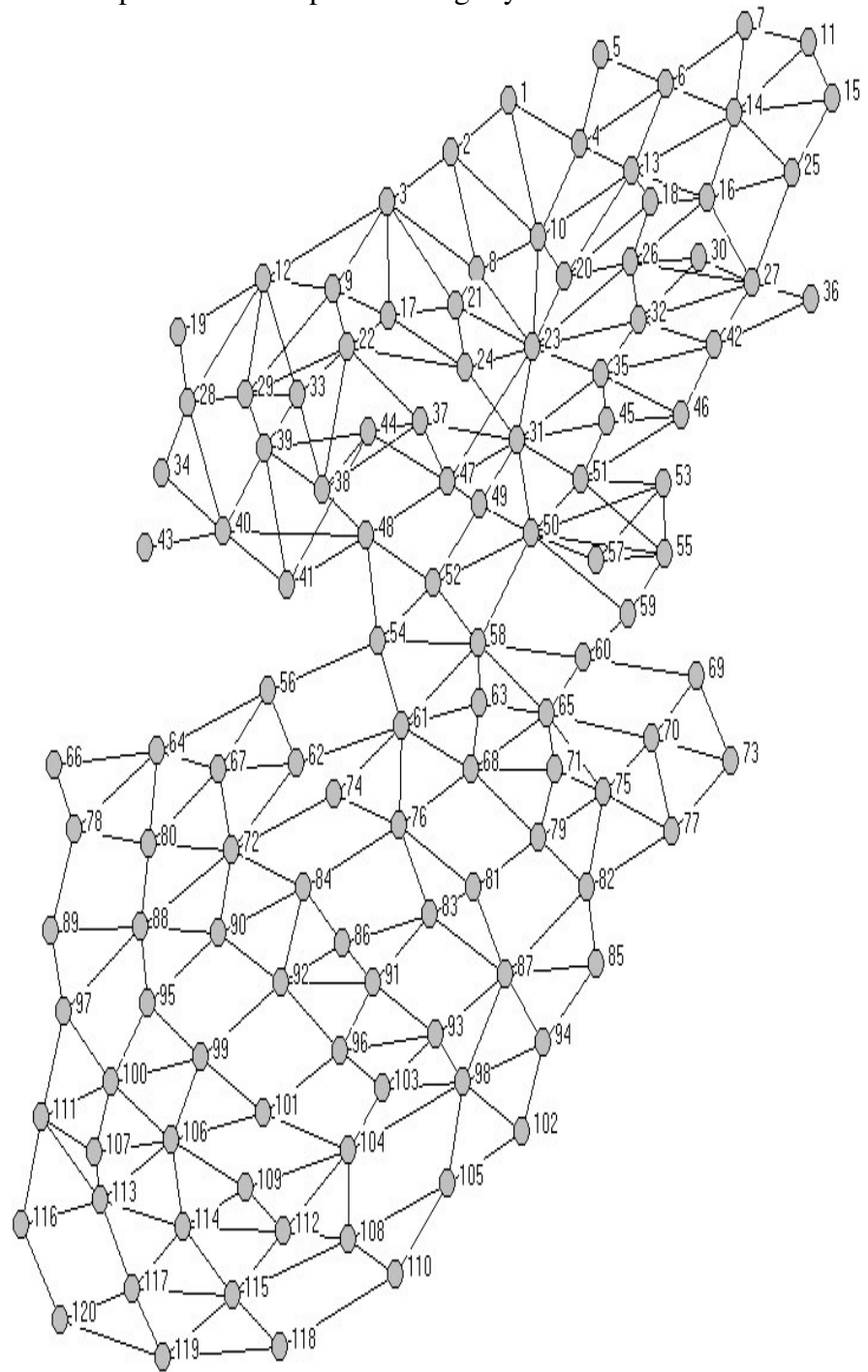Figure 4.4: Network Depiction of the Spatial Contiguity of Hollenbeck
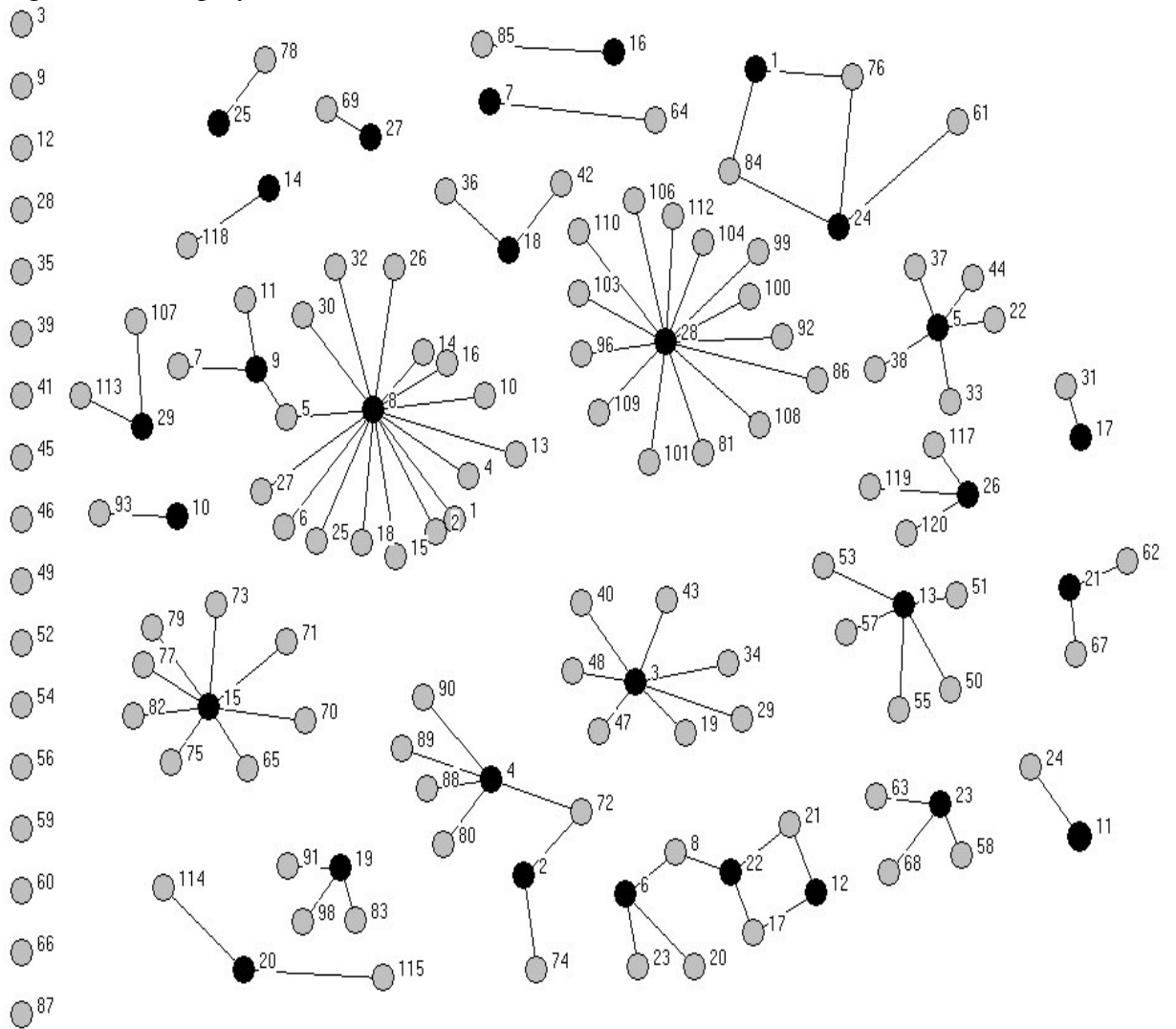
Figure 4.5: Gang-by-location network

Figure 4.6: Two-mode Matrix Linking Block Groups through Gang Rivalries
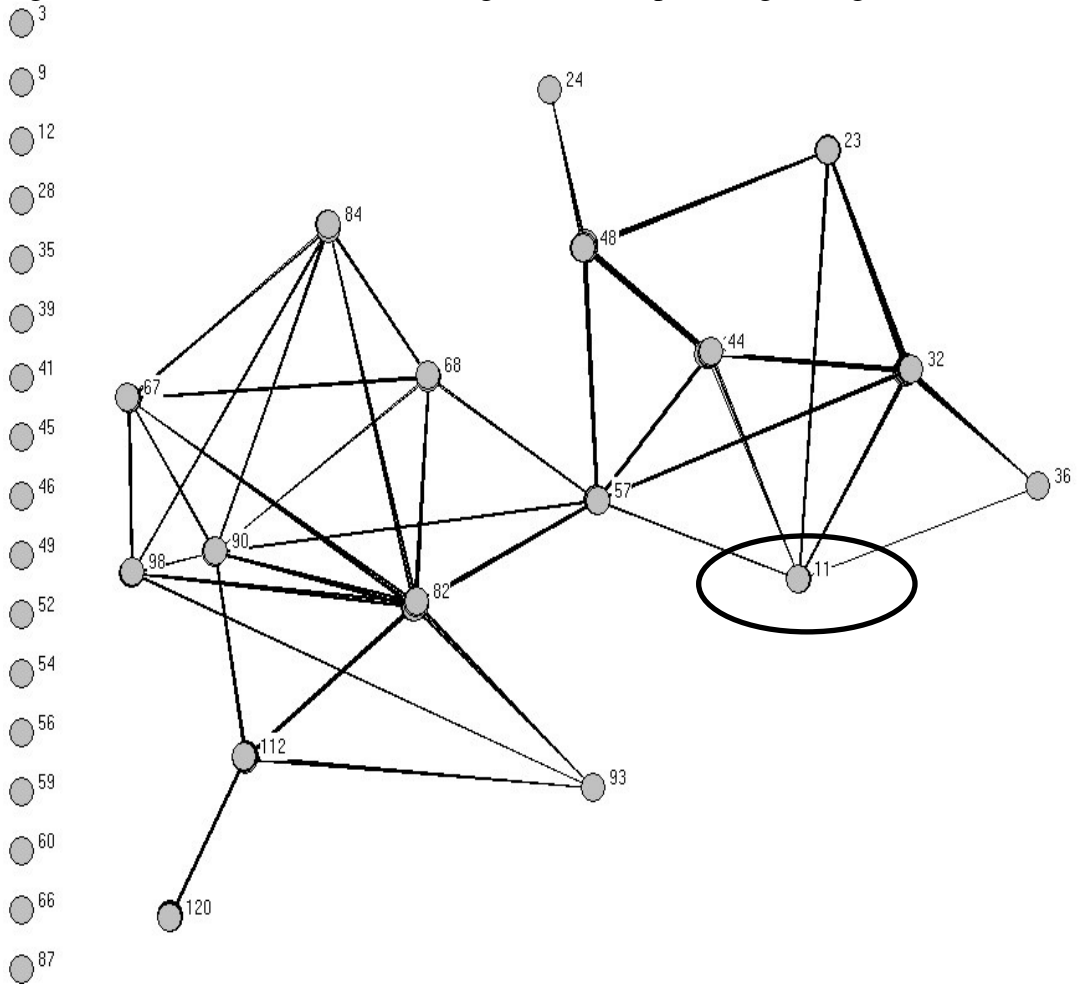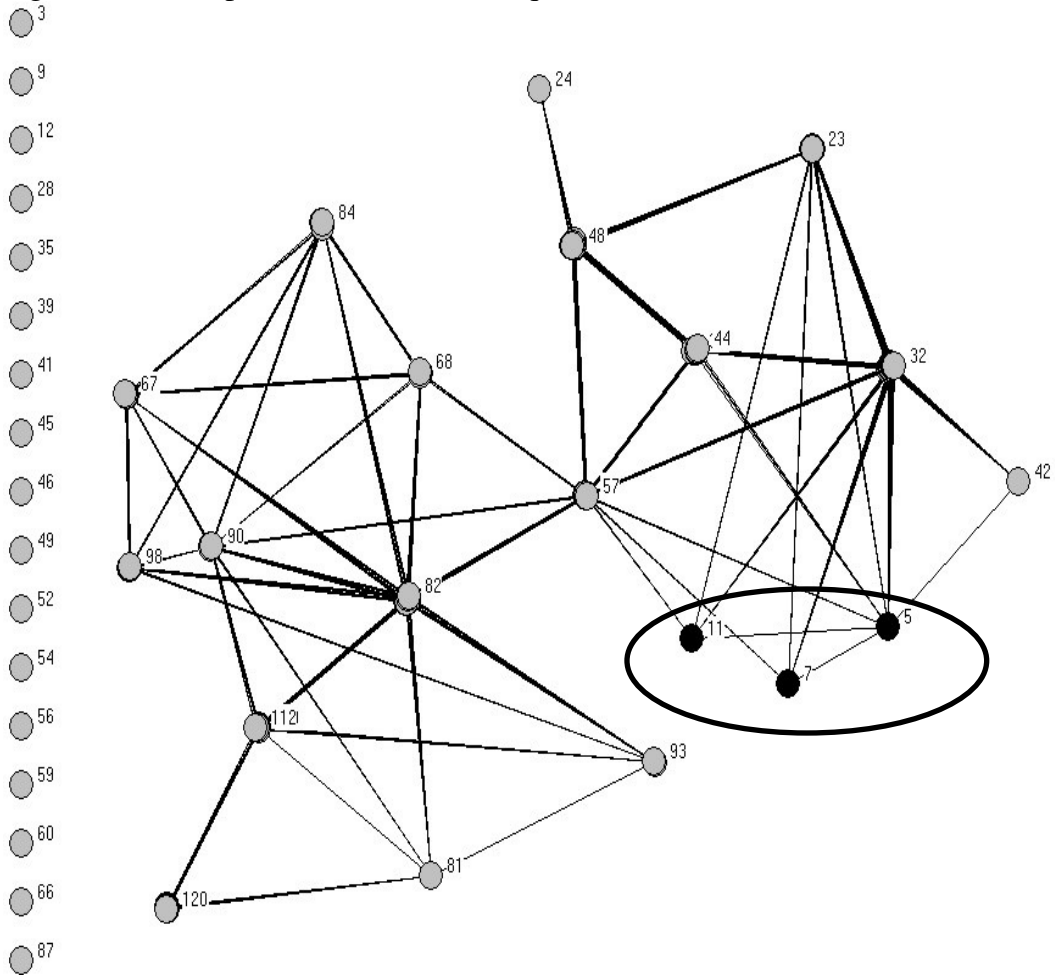
Figure 4.7: Example of the "Structural Equivalence" of Nodes

# CHAPTER 5

## SPATIALIZING SOCIAL NETWORKS: GEOGRAPHIES OF RIVALRY, TERRITORIALITY, AND VIOLENCE

This chapter, published in the *Annals of the Association of American Geographers* (Radil et al. 2010), blends concepts and techniques from social network analysis with conventional spatial analysis to theorize the socio-spatial processes involved in the 'hybrid' weights matrix from the previous chapter and to perform an analysis of the spatial patterning of violence using a social network analysis methodology. This research finds evidence for the production of differential spaces of violence in Hollenbeck, which I interpret as partial evidence of the social production of space, which is simultaneously made by the actions of the gangs and a mediator of further action by the gangs themselves. This paper is presented in this chapter unaltered from the published version aside from minor formatting changes.

INTRODUCTION

Social network analysis is an increasingly prominent technique in a number of social sciences and seemingly has obvious connections to geographies of networks and flows that have become popular in studies of globalization as well as identity politics (Murdoch and Marsden 1995; Dicken et al. 2001; Lantham 2002; Sheppard 2002). However, the compatibility of the techniques of social network analysis to geographic theories of networks has been challenged because of a lack of geographic nuance or consideration of the spatialities of power and other social relations in social networks (Allen 2003; Bosco 2006a). We recognize these shortcomings and explore the technique of structural equivalence in social networks as a means to incorporate theoretically

informed geographies of situation or embeddedness into social network analysis, a specific step in the broader project of integrating social theories of geography and spatial analytical techniques (Goodchild et al. 2000).

Specifically, we explore how an actor's position in geographic space can be analyzed simultaneously with their position in social networks. The geographic premise that social behavior is context-specific, and that space and society are mutually constituted, requires the incorporation of multiple spatialities into the analysis of social processes (Leitner et al. 2008). A typical social network analysis is a one-dimensional spatiality, identifying an actor's location in a social network. By spatializing social networks to include actors' simultaneous position in networks of relations and places we offer a technique to analyze the simultaneous embeddedness of actors in both network space and geographic space. The term embeddedness has become popular in discussing social networks to illustrate the many situations that social actors create and must negotiate in their behavior (Bosco 2006b). Embeddedness may be seen as a process of creating an increasing intensity of relationships (Bosco 2006b), but it is also a recognition that relationships, distance, and place-specific social relations are intertwined to situate actors (Sheppard 2002; Ettlinger 2003; Staeheli 2003; Leitner et al. 2008). Spatializing social networks facilitates the analysis of social behavior within the simultaneous and related contexts of network position and relative location in geographic space.

The ability of spatial analysis to incorporate the relative location of social actors, and the linkages between them, can, paradoxically, atomize actors being studied through a "spatial fetishism" that ignores or is unable to address the social relations that construct

the spaces within which actors operate.[23] Simply put, spatial analysis is good at analyzing clusters of social behaviors and phenomena (such as crime or disease) but struggles to illustrate the underlying causal structures and relationships. When spatial analysis is overly dependent on reasoning from spatial form to social process, the risk of reducing people to the spaces they occupy grows while the likelihood for new insights shrinks. A spatial analysis that is grounded in theories of the social construction of space and that can model the spatial patterning of relevant social relationships would represent a meaningful advance.

We argue that such an outcome is possible through making use of the concept of embeddedness and the related social network analytic technique of structural equivalence. By performing a hybrid analysis that integrates a spatial analytic approach into the analysis of social networks, we believe that we make a first useful step towards spatializing social network analysis while reducing the possibility of privileging space over social process. The technique we outline combines relative position in geographic space with social network position in a manner that identifies similarly situated actors in network and geographic spaces simultaneously. This in turn allows hypothesis development and evaluations of how differences in position in multidimensional spatialities may be said to relate to material outcomes. The technique and its ability to inform are illustrated by an analysis of gang violence in Los Angeles.[24]

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[23] This critique can be traced to Wolpert's (1964) behaviorist approach, but saw a more recent manifestation in Harley's (1989) critiques of the cultural norms within cartographic representations and Pickles' (1995) concerns of the unacknowledged representations in GIS. More recently Bosco (2006a) and Ettlinger and Bosco (2004) have noted the need to consider power relations in social network analysis. See also Collinge (2005: 191-201) for a contemporary discussion of spatial fetishism.

[24] This paper reports on initial findings in a collaborative project between geographers and a criminologist and extends the results of an exploratory spatial analysis of gang violence by the criminologist (Tita et al. 2003). The data used in this paper are the same as used in Tita et al. (2003).

In the following section, a discussion of embeddedness and how it relates to network perspectives and methods is offered. We then describe the study area and introduce the data used: a social network of gang rivalries and the geographic distribution of gang-related violence in the Hollenbeck Policing Area in Los Angeles, CA. We theorize territoriality, geographic embeddedness, and network position as the specific spatialities at work in the rivalry network and discuss how to consider these simultaneously. In the subsequent section, we present the results of a multi-relational positional analysis using social network methods. We conclude the paper with a discussion of the findings, which demonstrate that the spatialized social network is indeed a useful lens on gang violence in Hollenbeck. The geographic patterns in measures of violence in Hollenbeck are interpretable through and clarified by an understanding of the both the network and spatial relationships of the rivalry relations between gangs in the area. The technique demonstrated here has promise beyond this one study of gang crime. It operationalizes relational data in a way that allows simultaneous systematic evaluation of the way in which social actors' positionality in network relationships and spatial settings provide constraints and possibilities upon their behavior. In the conclusion we briefly explore how this technique can be further developed to allow for the addition of other spatialities into a systematic analysis.

EMBEDDEDNESS, SPATIAL ANALYSIS, AND SOCIAL NETWORK ANALYSIS

One particular way in which geographers have tried to understand the behavior of social actors (individuals, groups, organizations, or other social collectives) situated in specific contexts is through the concept of embeddedness. As noted by Ettlinger (2003),

Hess (2004) and others, the use of embeddedness in geography largely arose from the work of sociologist Mark Granovetter. In a parallel to calls for more 'spatialized' social science approaches (e.g., Goodchild et al. 2000), Granovetter (1985) argued for a more 'socialized' understanding of "the extent to which economic action is embedded in structures of social relations," and described what he called the argument of embeddedness: "that the behavior and institutions to be analyzed are so constrained by ongoing social relations that to construe them as independent is a grievous misunderstanding" (1985: 481–482). This idea of embeddedness as a form of structural constraint on social action made use of a reading of the word *embed* that implies a state of being surrounded tightly, enveloped, or otherwise constrained. However, another reading of the word embed suggests not just closeness but the state of something becoming part of an integral whole. Later Granovetter (1992) refined his arguments to differentiate between the kind of embeddedness that suggests closeness (which he called 'relational embeddedness') and the kind that suggests the importance of position in a larger whole ('structural embeddedness').

Both perspectives on embeddedness have been important for geography. Embeddedness as closeness has resonance for geographers that explore the themes of geography, space, and place as contexts with implications for human behavior. Entrikin offers a helpful example with the claim that "my life is always embedded in the story of those communities from which I derive my identity'' (1991: 9). For Entrikin, the 'embeddedness' of being within a place-specific social milieu is inseparable from the particulars of human activity. Entrikin's sentiments also reflect Pred's (1984) theoretical understanding of place as a historically contingent process. Embeddedness as position in

a larger social structure is also an emerging theme. For example, Flint argued that space is partly produced by the "connections [of a given place] to the rest of the world" (2002, 33) and that, presumably, different connections lie at the heart of the production of different kinds of spaces. In fact, as Staeheli (2003) points out, this perspective on space blurs with concepts of place in geography. Although space has historically been understood as referencing the general or universal in geography, as Staeheli notes, contemporary concepts of the social construction of space leads to a refocus from the universality of processes across space to the unique outcomes present in different spaces: spaces become 'social locations' embedded in "webs of cultural, social, economic, and political relationships" (Staeheli 2003: 160). From this perspective, the distinctiveness of spaces/places is due to the 'embeddedness' of being differently located in larger social structures.

As Granovetter (1992) suggests, these different perspectives on embeddedness are not mutually exclusive or necessarily discrete categories, but rather points that blend into the other. As such, both may be seen as important elements in geographic arguments about the social production of space and how geography mediates social behavior in places. For example, when Agnew (1987) described places as composed of three related elements (locale, location, and sense of place), embeddedness as closeness is similar to Agnew's description of locale as "the settings in which social relations are constituted," while embeddedness as position is similar to Agnew's notion of location as "the geographical area encompassing the settings for social interaction . . . at a wider scale" (1987: 28). Massey (1993: 66) provides another useful example: her power-geometry concept is concerned with the position of individuals and social groups relative to the

spatial flows of people, information, and capital between places while her progressive sense of place concept incorporates both kinds of embeddedness, emphasizing the role of social relations that are both "in a situation of co-presence" and "stretched out over space." Drawing on these lines of thinking, social behavior can be understood as affected and produced not just by the specific embedded practices, conditions, institutions, or identities of a single place, social location, space, or geography, but also by the way these features are in turn affected and produced by the specific embedded practices, conditions, institutions, or identities of other places, social locations, spaces, or geographies to which they are connected.

Many kinds of spatial analysis make use of the concept of embeddedness as closeness. For example, spatial econometric models consider the influence of places on each other by formalizing the geographic connectivity between the units of analysis which is used to create new variables for inclusion into statistical models (Anselin 2002). More plainly, the degree to which a focal spatial unit is embedded in its closest neighboring geographies is modeled, usually either by identifying its areal contiguity with other spatial units or by selecting neighbors based on the smallest geographic distances between them. Beyond the issues of spatial fetishism, there are some meaningful limitations to this particular approach. All the processes that might contribute to the production of certain spatial patterns are modeled in the same fashion — by using the relative location of each unit of analysis. For example, in an analysis of U.S. crime patterns aggregated to the scale of counties, Baller et al. (2001) accounted for all the processes of social interaction between counties by defining a set number of the nearest counties (measured by the geographic distance between the approximate center of each

county) as influential neighbors for a given focal county. Then, crime data from the set of influential neighbors were used to create a "spatial lag" variable that was included with other explanatory variables for regression modeling (Baller et al. 2001).

In this example, embeddedness is simply the degree to which each county exhibits similarity in crime and location. If the social relationships that are theorized to underlie a particular observed geographic form are one of embeddedness as closeness, then the model used by Baller and his colleagues may be an appropriate choice. What this approach does not allow is a consideration of any spatiality that cannot or should not be operationalized through an examination of the qualities of the closest units in geographic space. This limitation is meaningful because as observed by Leitner et al. (2008), multiple spatialities are bound up in issues of interest to geographers and these should be examined together where possible. Ettlinger (2003: 161) emphasized similar themes when describing what she refers to as overlapping networks: "the intersection of different networks in which individuals are engaged," where each network may be thought to represent different kinds of relationships and where only some relationships are "based on proximity." Kwan (2007) also argues that the complexity of human spatial behavior cannot be captured in spatial models with a single type of spatial measurement, such as distance. Quantitative analytic techniques that allow for the consideration of more than a single kind of embeddedness, including position within a social network, would be an important step in addressing the concerns noted above.

Embeddedness that is based upon occupying a particular position within a network is a central concept within sociology. Since the work of Georg Simmel (Simmel 1955: see also Breiger 1974 and Grabher 2008) in the late 19th and early 20th centuries

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to the very present, one of the primary goals of social network analysis has been to formalize and model the theoretical concepts of social position and to "reveal subsets of actors that occupy equivalent social positions" (Freeman 2005: 248). Social position refers to a collection of actors who are similar in social activity or interactions with respect to actors in other positions; in other words, a social position is "defined by a collection of actors who are similarly embedded in networks of relations" (Wasserman and Faust 1994: 348).

Investigating the effects and consequences of different social positions is a major theme in the social network literature. For example, Friedkin (1984) applied the relative contributions of positions to the study of social homogeneity, finding equivalence on multiple relations to be a useful indictor of group homogeneity. Other notable examples include Snyder and Kick's (1979) examination of the positions of states in international trade networks and Burt's (1987) look at the effect of positions in networks of professional relationships on the adoption of new drugs by physicians. The unifying theme across these different research topics and domains is the assumption that structural position in a social network is an important factor in understanding how actors behave and influence one another.

For social network analysis, similarly patterned actors are seen as occupying distinct 'social positions' in network structures, which is to say that they are similarly embedded in the webs of relationships that constitute the social network in terms of links to other actors (Granovetter 1985; Wellman 1988; Wasserman and Faust 1994). As one of the primary goals of social network analysis is to formalize the theoretical concepts of social position (Freeman 2005), social network analysis is a useful way to explore the

concepts of embeddedness in a quantitative fashion through highlighting different social positions as realized in networked data. However, as Bosco (2006a) and others have observed such network analyses are largely devoid of any geographic specificity. Positions in network space are rarely considered in a way that attempts to incorporate the actual geography of the network while geographers tend to think of embeddedness in purely 'territorial' ways.[25]

In network analytic terms, structural equivalence is one of the most common concepts and methods used to identify different social positions in a network of actors (Doreian et al. 2005). Actors in a network are said to be structurally equivalent if they have identical ties to and from the same other actors in the network (Lorrain and White 1971). Strict structural equivalence is a mathematical property of nodes in a network and typically unrealized in real data. For this reason the common approach in network-based analyses is to identify actors who are "approximately structurally equivalent" (Wasserman and Faust 1994: 366) or to employ variations on structural equivalence.[26] Identifying social positions as collections of actors with similar measures of equivalence allows theories of similar behaviors and outcomes for similar actors to be operationalized

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[25] In this sense, 'territorial' means an emphasis on geographically local relations (see Ettlinger 2003 and Hess 2004). In a related critique, Bosco's (2006b) discussion of embeddedness warns against focusing on simple measures, such as whether ties in a network are weak or strong, or the actual geographic distance separating actors. In his qualitative analysis, the situation of actors in places that are themselves situated in broader networks is identified as a key feature of the situation of actors. A quantitative analysis of social networks will struggle to uncover the precise mechanisms by which a few actors developed their position in a network as well as the role of emotions in social behavior, both important features of Bosco's (2006b) work. However, the conclusion that "network processes are affected by, and cannot be divorced from, the conditions governing the context in which they are produced and in which they operate" (Bosco 2006b: 360) is one that indicates a role for quantitative analysis in identifying the interaction between geographic and network spaces in contextualizing social behavior. Hence, and in a complementary fashion, a quantitative analysis of social networks can attempt to integrate the insights gained from contemporary social theory regarding space and geography (Goodchild et al. 2000).

[26] The two most common approaches to equivalence are structural equivalence and regular equivalence. The most important difference between the two is that structural equivalence requires that equivalent actors have the same connection to the same neighbors while regular equivalent actors have the same or similar patterns to potentially different neighbors (Doreian et al. 2005).

and tested. These sorts of questions are drawn from theories of social influence which generally posit that identically positioned actors in a relational network use each other as a frame of reference for appropriate behavior even if the actors have no direct interaction with the other (Burt 1987: 1293). From this perspective, influence is directly tied to the perception of what constitutes proper actions for actors in specific network positions (Galaskiewicz and Burt 1991).

Network-based operationalizations of theories of social position offer potential insight into the spatiality of social behavior. We begin with the recognition that space is socially constructed, and emphasize that part of the construction process relates to the simultaneous geographic embeddedness and network position of actors. Conceptualizing the geographic spaces within which actors are embedded as a kind of relational network and using the ability of network methods to identify similarly positioned actors can lead to a consideration of the spatiality of these networks. In other words, combining geographic and social networks in such a way that identifies differently structured spaces (beyond just a consideration of the relative location of these spaces) may offer insight into the relational nature of space and how measures of equivalence relate to specific behavioral outcomes in different spaces of social position.

We call this approach *spatializing social networks*. As an analytic framework, this approach allows influence to take place not just between geographically proximate neighbors (as with conventional spatial analysis) but also between actors that are close in terms of social network space. We see this as a first step toward addressing the complex nature of embeddedness (Bosco 2006b) and considering more than one spatiality of embeddedness (Leitner et al. 2008). Spatializing social networks allows the identification

of *structurally equivalent geographies* along multiple relational spatialities; hypotheses of structured outcomes between and among spaces with similar social positions may be then tested empirically. The aim of this approach is a systematic consideration of the role of actors' embeddedness in space and network positionality as a partial explanation of their behavior.

## STREET GANGS, RIVALRIES, AND TERRITORIALITY IN HOLLENBECK

This study focuses on violence involving urban street gangs in the Hollenbeck Community Policing Area in Los Angeles, CA.[27] Located east of downtown Los Angeles, the Hollenbeck Policing Area "has a population of roughly 200,000 people and is 15.2 square miles in size. It encompasses the communities of El Sereno, Lincoln Heights and Boyle Heights" (Los Angeles Police Department 2008). According to U.S. Census statistics, most of the population is Latino (84.5%) and nearly forty percent (39.4%) of the total population was born in Mexico. Thirty percent of the population lives below the poverty line and of the total population that is at least twenty-five years old, thirty five percent has less than a high school degree or equivalent (Tita et al. 2003).

According to Tita et al. (2003), homicide rates in Hollenbeck have been higher than both Los Angeles and U.S. national homicide rates since the early 1990s. Hollenbeck consistently ranks among the top three or four of the Los Angeles Police Department's (LAPD) 18 policing areas in violent crime. LAPD crime statistics for 2007

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[27] The Los Angeles Police Department (LAPD) has a geographic structure that organizes policing activities. The LAPD divides Los Angeles into 18 different geographic regions, called Community Policing Areas. These Community Areas are organized into one of four Bureaus. Hollenbeck is one of five Community Areas in the LAPD's Central Bureau. See http://www.lapdonline.org/hollenbeck_community_police_station and Tita et al. (2003).

show that violence in Hollenbeck remains high as there were 799 violent crimes reported in the Hollenbeck area, which translates to 4.7 percent of the citywide totals for violent crimes in that year (Los Angeles Police Department 2008). Gangs and gang-related issues are central to violent crime in Hollenbeck: gangs were involved in nearly 75% of all homicides in Hollenbeck from 1995 to 1998 (Tita et al. 2003) and in a 2008 report by the Los Angeles County District Attorney, the Hollenbeck Policing Area was classified as an area of "Very Heavy Gang Activity," the highest category of the classification scheme used in the report (Cooley 2008: 45).

Tita et al. (2003) argues that the combination of physical barriers and political geographic boundaries that define the Hollenbeck area serve to limit interactions with gangs from neighboring areas. As seen in Figure 5.1, Hollenbeck is delimited in the west by the Los Angeles River and along the northwest by the Pasadena Freeway. The city of Vernon, CA, which lies to the immediate south of Hollenbeck, is an industrial area with a total population of only 91 at the 2000 census. Thus, there no are spatially proximate gangs in either of these directions. To the southeast, Hollenbeck is bordered by an unincorporated area of Los Angeles County (East Los Angeles). To the northeast, Hollenbeck shares a border with the city of Pasadena. Both of these areas do have urban street gangs, yet none of these gangs are rivals with any of the Hollenbeck gangs. There are several reasons for this. First, although no physical barrier serves to impede movement between Hollenbeck and either East Los Angeles or Pasadena, the fact that each is served by different public school districts greatly restricts across-place social interactions (Grannis 2009). Though every other gang in the region may be a potential rival, with no history of interaction among local youth, the gangs outside of Hollenbeck

remain outside of the awareness space of the Hollenbeck gangs. Second, there exists a simple propinquity effect as none of the gangs found in either East Los Angeles or Pasadena occupy space on the border shared with Hollenbeck. The net effect of these border features, both physical and political, is to create a landscape within which the rivalries of the Hollenbeck gangs are wholly contained (Tita et al. 2003).

Hollenbeck is no stranger to gangs and gang activity. The history of urban street gangs in east Los Angeles, including Hollenbeck, is a long one, with some gangs documented back to the late 1940s (Moore 1991). From 2000 to 2002, 29 active gangs were identified in the Hollenbeck area (Tita et al. 2003). Control over territory is a central theme for the gangs of Hollenbeck. The gangs in Hollenbeck are what Klein (1995) describes as 'traditional' in that they have a strong attachment to turf, or the territory under the direct control of a gang. Tita et al. (2003) makes a similar argument and characterizes the gang violence in Hollenbeck as expressly tied to the defense of turf and control over territory. Although they arise from different motivations, the anti-gang activities of the LAPD also revolve around control of territorial space. As described by Herbert (1997) "police (LAPD) strategies to create public order involve enacting boundaries and restricting access" (1997: 11). The key point here, made by Sack (1986) and others (e.g., Paasi 2003), is that territory is not the static result of social processes but is instead what Newman calls an "imperative" and an "essential component of human behavior" (2006: 88-89). The attempts by the various gangs to control the spaces of Hollenbeck result in violence between the different street gangs themselves. Understanding the spatial patterning of the relationships between the gangs, themselves

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wrapped up in issues of contesting and controlling space, are key to understanding the spatial patterning of gang violence in Hollenbeck.

The emphasis on territorial control by gangs in Hollenbeck relates to a key way in which spaces and places are socially constituted. In geography, territoriality is often seen as the "delimitation of boundaries" and the interrelated "behavior within those boundaries" (Kahler 2006: 2). Robert Sack's (1986) influential work on territoriality defines it as the use of territory for political, social, and economic ends and it has been most often associated with the spatiality of the nation-state (Paasi 2003). We can say that territoriality is conventionally understood in geography as involving both a partitioning of space into distinct units and ongoing attempts to control the space in order to maintain the borders between the units (Kuus and Agnew 2008). These characteristics track well with how Tita describes gang turf: a well-defined geographic area of a city, such as a neighborhood, that is claimed by the gang as its 'domain' (Tita et al. 2005).

Territoriality as domain and partitioning behavior leads Newman (2006: 91) to conclude that territorial behavior is quite meaningful at "local levels": "rivalries are played out through the daily life practices of segregated groups residing in their own distinct . . . neighborhood turfs." Both Newman's (2006) emphasis on spatial segregation and Cresswell's (1996) work on places as geographic expressions of cultural norms and transgression to those norms suggests a reason why the persistent territoriality of Hollenbeck's various gangs might result in violence between them. When a gang member enters the turf another gang, a spatial transgression has occurred and the gang member is now "out of place." In these situations, the response to such spatial transgressions may involve violence. If presence in other turfs can be seen as transgressive, there is an

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expectation that local geographic embeddedness or the relative nearness to differently controlled spaces is an important element to certain kinds of outcomes, such as violence (Kahler 2006).

MAPPING GANG VIOLENCE IN HOLLENBECK

As described in Tita (2006), from 2000-2002, Hollenbeck experienced 1,223 violent crimes by or against gang members. This kind of violence is defined by Tita (2006) as 'gang related' and includes the protection of turf from an incursion by rival members as well as all other violence involving a gang member. The list of crimes over this time period include the legal classifications of aggravated assaults, simple assaults, assault with a deadly weapon, attempted homicides, homicides, robberies, kidnappings, and firing a gun into an inhabited dwelling/vehicle.[28] When aggregated by U.S. Census block groups, mapping the violent crimes suggest two important features (see Figure 5.2). First, violence has penetrated all areas of Hollenbeck and, second, there may be some spatial clustering of gang-related violence.

The first point is straightforward as violent crimes were present in every block group. Incident counts by block group range from a low of 1 (occurring 6 times) to a high of 44 (occurring once) with a mean across block groups of 10.19. To evaluate the second observation, a global Moran's *I* test of spatial autocorrelation was performed by identifying block groups as neighbors on the basis of either sharing a common length of border ("rook"

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[28] Rape and domestic violence reports were not available and not included in violence counts (Tita et al. 2003).

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contiguity) or sharing a single border point ("queen" contiguity).[29] Despite the presentation in Figure 5.2, neither rook nor queen configurations resulted in strong statistical measures of dependence (see Table 5.1). The Moran's *I* ratios of 0.09 for rook and 0.08 for queen are interpreted as very weak positive dependence (positive dependence means neighboring values are similar). In fact repeating the test by increasing the contiguity from first-order neighbors (those that share border lengths or points) to also include second-order neighbors (neighbors of the first set of neighbors using the same criteria of shared border length or point) results in measures that are interpreted as very weak negative spatial dependence (neighboring values are dissimilar; Moran's *I* ratio's of -0.09 for 2nd order rook and -0.04 for 2nd order queen). While the absence of evidence for robust global spatial dependence may be due to the level of aggregation in the data, it also does not recommend a conventional spatial analytic approach.

GANG RIVALRY AND TERRITORIAL NETWORKS

Tita et al.'s (2003) analysis of violence pertaining to the 29 different gangs active in Hollenbeck from 2000-2002 identified a social network of gang rivalries. Rivalry is a meaningful relation in this circumstance as urban street gangs are committed to the defense of their turf and have negative relationships (i.e., rivalries) that explicitly tie them to other gangs (Tita et al. 2003). This interpretation is related to implications of rivalries as a key social relation in the attempt to understand other forms of violence (see Diehl and Goertz 2000 and Flint et al. 2009 for examples). The rivalry relations were identified through the use of a survey by Tita et al. (2003) that asked informants from both the

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[29] Contiguity matrices and Moran's *I* tests were constructed and performed using the GeoDa spatial econometric software package (Anselin et al. 2006).

LAPD and some of the gangs to identify the rivalries between each of the gangs.[30] A network diagram of these rivalries is shown in Figure 5.3. The nodes in this network represent the gangs and the connections between them represent the rivalries. The measurement of rivalry was binary where the presence of a rivalry resulted in a link and the absence of a rivalry resulted in no link. Every gang was connected to the network structure and the number of rivalries ranged from a minimum of 1 to a maximum of 10. As is common in network analyses, the network can also be described as a matrix. In this case, a $29 \times 29$ binary matrix was produced where the presence of a rivalry between the gangs was coded as 1 and the absence of a rivalry was coded as 0 (Tita et al. 2003).

In addition to identifying gang rivalries, the location and boundaries of the turf of each of the 29 gangs was mapped through the participation of the LAPD (Tita et al. 2003). Tita (2006) later used U.S. Census block group areal units to establish the presence or absence of gang turf at a geographic level that possessed data of interest to ecological studies of crime. The Hollenbeck area is comprised of 120 such block groups and gang turf was present in 103 of these units. In seven instances, more than one gang claimed turf in the same block group. However, close spatial proximity was not always a predictor of rivalry (Tita 2006).

After identifying both a social network of rivalries and the relative geographic locations of gang turf with a disaggregated territorial map, Tita (2006) made a unique methodological choice by attempting to blend these structures together. This was done by

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[30] Rivalry relationships between the gangs were identified through the use of a survey of local police and former gang members by Tita et al. (2003). Each informant was provided with a survey comprised of one page for each gang. At the top of the page, a particular gang was identified and the respondent was asked to 'Please Identify All of the Gangs that are an **Enemy** of the <insert gang name>.' Law enforcement experts and several current and former gang members completed the survey and there was perfect agreement across the gang members' and law enforcement experts' surveys.

first reimagining the geography of gang turf as a network of neighbors, a conventional way to produce a 'spatial weights matrix' for use in spatial econometric models (Anselin 2002). Each areal unit of Hollenbeck (census block groups) became a single node in a new network and the links between the nodes were based on geographic contiguity. The coding scheme was again binary where block groups that shared borders are formally connected while those that do not remained unconnected. After distributing the gang rivalries to the disaggregated territorial map, the two separate network matrices ($29\times29$ gang rivalries and $120\times120$ census block groups) were then associated using matrix multiplication to produce a single $120\times120$ matrix for use in a spatial econometric model. This weights matrix was then used to create a new explanatory variable, which was included in a regression along with a variety of other common measures in criminology, such as education and income (Tita 2006).

Tita's (2006) use of the hybrid weights matrix as the connectivity input for a spatial econometric regression model was an innovative approach in the spatial econometric modeling of crime, but it also kept at arm's length one of the central claims of relational social science - that relationships between actors have more explanatory power than do attribute-based categories (Emirbayer and Goodwin 1994; Emirbayer 1997). Despite using relational data (the relative locations of the gangs and the rivalry relationships), the initial analytic product was another attribute-based explanatory variable and the analytic focus remained on the perceived causal power of attributes. Additionally, and most importantly for this paper, this approach forced network position to be modeled as local geographic embeddedness. In other words, the theoretically distinct spatialities of embeddedness were operationalized as a single form of

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embeddedness and all interactions between the geographic units of analysis became overly 'territorialized' (Hess 2004).

The lack of fidelity to the explanatory power of relationships along with the fact that both the spatialities of geographic embeddedness and network positionality must be operationalized in the same way leaves something to be desired. On this basis and by drawing on Anselin's (2002) observation that the construction of the spatial weights matrix in spatial econometric models is actually based on social network concepts, the authors began a series of conversations that extended Tita's previous analysis while engaging theoretical discussions of embeddedness. In this paper, the particular outcome is a consideration of whether structural similarity based on both kinds of embeddedness contributes to similar outcomes for actors.[31] We examine this question in a way that that fits the spatialities under consideration. The hypothesis here is whether or not similarly embedded and positioned territorial spaces experience similar amounts of violence. In other words, can structurally equivalent geographies be identified from both the embedded gang turf and the rivalry network that connects them and do differently structured geographies exhibit different violence patterns?

## SPATIALIZING THE SOCIAL NETWORKS OF HOLLENBECK'S GANG RIVALRIES

Positional analyses involve identifying social positions in a relational network based on similar patterns of links between individual nodes. The process is well

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[31] See Leenders (2002) for a discussion of the nature of the spatial weights matrices in spatial econometrics and similarities with social network analysis.

developed in social network analysis and most positional analyses "focus on identifying subsets of equivalent actors" (Wasserman and Faust 1994: 354). Identifying subsets in a complex network involves simplifying the networked data. Whether presented as a network diagram or a matrix, it is difficult to visually identify meaningful patterns that may exist. For example, the spatialized rivalry network is shown in Figure 5.4. The complexity of the ties precludes visual interpretation. However, a matrix of spatialized rivalry relations may be reorganized on the basis of similar ties between actors in the network. This activity is referred to in network terms as matrix permutation and allows similar actors to be grouped together (Wasserman and Faust 1994).

As previously discussed, relationships between the 29 different gangs of Hollenbeck may be represented in matrix form. However, the rows and columns of the resulting $29 \times 29$ matrix represent both a social unit (gangs) and a territorial unit (turf). As such, there are two distinct spatialities of embeddedness that must be considered: local geographic embeddedness and position in the overall network structure. Geographic embeddedness, especially among territorial units with demarked boundaries and that are mutually exclusive of other units (such as gang turf), can be represented in the conventional spatial econometric way through a consideration of relative location. Neighboring gang turf (those that comprise the geography in which a given gang's turf is embedded) can be identified through shared borders. The rivalry network can be represented in a similar way, with rivalries between gangs coded in the matrix. The result is two $29 \times 29$ matrices, one for each spatiality.

While the $29 \times 29$ matrices capture all the social and territorial units identified by Tita et al. (2003) in the Hollenbeck Policing Area, the matrices do not capture the entire

geography of Hollenbeck. There are areas of Hollenbeck that are not claimed as turf by any of the gangs but that do experience gang-related violence. Although these areas of Hollenbeck do not represent the territorial claims of the gangs, we include these areas into both the geographic embeddedness matrix and the network positionality matrix. An important reason for this choice is that some of the gangs do not share borders with other gangs and are instead bounded by unclaimed areas. However, these unclaimed areas still must be negotiated in some sense to reach the turf of other gangs and therefore may be understood as a kind of connective tissue to the overall gang geography (see Tita and Cohen 2004: 199). Further, as an empirical reality, gang-related violence is not wholly contained within claimed turf and excluding unclaimed areas would also involve excluding information that could affect the outcome of the analysis. More plainly, a consideration of local geographic embeddedness that did not include unclaimed spaces would be partial and incomplete. For these reasons, the unclaimed areas were included by simply adding another row and column to each matrix. In the case of the geographic embeddedness matrix, the unclaimed areas were treated as another possible neighbor in the embedded geography of the gang turf. For the network positionality matrix, the unclaimed areas never resulted in a link as they did not represent a social unit that another gang could have a rivalry with. The final result was two binary $30 \times 30$ matrices.

The identification of equivalent geographies on the patterning of ties of both geographic embeddedness and network positionality was accomplished using the network analysis program UCINET (Borgatti et al. 2005). The particular technique used for this study is called 'convergence of iterated correlations' or CONCOR (Breiger et al. 1975; see also Wasserman and Faust 1994: 376-381). This procedure computes Pearson

product-moment correlation coefficients among the rows and columns of the input

matrices by comparing the value of a given cell to the mean value of both the row and

column in which it occurs.[32] The result is a new single matrix where cell values are the

calculated correlation coefficients which is meant to represent the structural similarities

between pairs of actors based on similarities in the patterns of the ties between them.

Actors that are perfectly equivalent on all relations will have correlation coefficients of

$+1$ between their rows and columns of the original input matrices. However, as noted

earlier, perfect equivalence rarely occurs in most actual network data. For this reason, the

CONCOR process uses the correlation matrices as input for a new round of correlation

computations. The output from this calculation is used as input for yet another round of

correlations, and the process continues in this fashion. As noted by Wasserman and Faust

(1994: 377), "after several iterations of this procedure, the values of all correlations in the

matrix are equal to either $+1$ or $-1$."[33] The final correlation matrices are dichotomized

to allow all actors to be grouped into one of two categories. In network terms, actors in

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[32] Correlations are not the only method to identify equivalences in a network. It was chosen for this study as it is identified by Wasserman and Faust (1994) as the preferred measure for pattern similarities. The formula for calculating correlations on a single relation between an actor $i$ and an actor $j$ is

$$r_{ij} = \frac{\sum (x_{ki} - \bar{x}_{\bullet i})(x_{kj} - \bar{x}_{\bullet j}) + \sum (x_{ik} - \bar{x}_{i\bullet})(x_{jk} - \bar{x}_{j\bullet})}{\sqrt{\sum (x_{ki} - \bar{x}_{\bullet i})^2 + \sum (x_{ik} - \bar{x}_{i\bullet})^2} \sqrt{\sum (x_{kj} - \bar{x}_{\bullet j})^2 + \sum (x_{jk} - \bar{x}_{j\bullet})^2}}$$ where $\bar{x}_{i\bullet}$ is the mean

of the values in row $i$ of the matrix (excluding the diagonal) and $\bar{x}_{\bullet i}$ is the mean of the values in column $i$ of the matrix (excluding the diagonal). This formula can accept matrices coded as 0 or 1 as it subtracts mean row and column values from the focal unit cell values. Calculating correlations on multirelational data is done using a generalized version of the formula for single relations:

$$r_{ij} = \frac{\sum_{r=1}^{2R} \sum_{k=1}^{g} (x_{ikr} - \bar{x}_{\bullet i})(x_{jkr} - \bar{x}_{\bullet j})}{\sqrt{\sum_{r=1}^{2R} \sum_{k=1}^{g} (x_{ikr} - \bar{x}_{i\bullet})^2} \sqrt{\sum_{r=1}^{2R} \sum_{k=1}^{g} (x_{jkr} - \bar{x}_{j\bullet})^2}}$$ where there are $r = 1, 2, \ldots, R$

relations (Wasserman and Faust 1994, 368-369). The result for both formulas is a single matrix where the non-diagonal cells are correlation coefficients. Our study uses two matrices as inputs - one for geographical embeddedness and one for network position.

[33] The default number of iterations in UCINET is 25 and this was used for this analysis.

the same category are similarly structured in the network, which is the functional definition of equivalence.

The CONCOR process also allows analysts to define the number of positions to identify. For example, the process will identify exactly two social positions for all of the actors in a given multi-relational network. This may be a useful generalization, but it may also be an oversimplification and the analyst may desire to identify more detailed patterning. This can be done by performing another round of CONCOR to sub-matrices of the original data, which are comprised of the actors of each of the two positions identified in the first round as described above. In other words, all the actors from each category are reorganized into new and separate matrices (one for each relation) and the CONCOR process begins again to each of these new sets of matrices. Each set of matrices are split into two positions again; two becomes four, four becomes eight, and so on.[34]

For this study, the CONCOR process was applied three times, which produced eight positions. As mentioned above, more positions could be identified up to a maximum of 30.[35] However, in keeping with the overall goal of a positional analysis to simplify patterns, it was concluded identifying more than eight positions could be counterproductive. A common way to represent the product of the CONCOR process is

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[34] The CONCOR procedure always splits a set of actors into exactly two subsets and repeating the process results in a series of binary splits. This has been critiqued in the social network literature as imposing a form on the identification of social positions that may not connect well with theory (Wasserman and Faust 1994, 380). This critique can be seen in this study as imposing a hierarchical structure to the gang turf geography. Even in an exploratory study such as this one, this issue is worth noting and future efforts along these lines would benefit from comparing the positions identified by CONCOR with those identified by other commonly used techniques. See Borgatti and Everett (1992) for a helpful discussion of the challenges in matching the methods used to identify social positions with the different theoretical concepts of equivalence in social network analysis.

[35] Because each matrix contained only 30 rows and columns, the maximum number of possible equivalence categories is 30 which would occur when each row/column in the matrix becomes its own unique category.

with a dendrogram. The dendrogram that resulted from applying the CONCOR process three times to the spatialized rivalry data is shown in Figure 5.5. Each of the 30 units in the two relational matrices was classified into one of eight positions, many of which were comprised of multiple gangs. Only two positions were made up of a single gang or unit of analysis: after the third split, the unclaimed areas of Hollenbeck were identified as a unique geography as was the turf of one of the gangs (see Figure 5.5).

Each time the CONCOR process was applied, two further analytic steps were taken to interpret the results. First, the resulting positions were mapped using a GIS to aid in understanding and describing the overall geography of the equivalence categories. Second, analysis of variance tests were performed on violence counts to determine statistically significant differences between the geographies identified by each CONCOR iteration.[36] Statistically significant results suggest that the observations on violence are drawn from different populations. We interpret this not just as empirical evidence of differences in the amount of gang-related violence between differently embedded and positioned geographies but also as evidence of different social processes at work. The results of each split and of the associated analysis of variance tests are described below and presented in Table 5.2.

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[36] Parametric and non-parametric analysis of variance (ANOVA) tests were performed and results of each are reported in Table 2. The non-parametric test used is the Kruskal-Wallis test which uses ranks in place of actual data. The Kruskal-Wallis test, like all rank-based statistics, lacks resolving power (as seen by the second and third split results in Table 2) but is generally considered robust against non-normal data, such as the count data we used. The census block group geography used by Tita et al. (2003) and Tita (2006) was retained for the analysis of variance tests. Counts were aggregated by census block group (n = 120) and each block group was coded to one of the 29 gangs. Block groups that were outside any gang turf were coded as part of the single unclaimed area unit previously described.

RESULTS

*First Split*

The first application of CONCOR resulted in the identification of two differently structured positions based on patterns of geographic embeddedness and network positionality. As seen in Figure 5.6A, these positions result in a clear north-south division in the gang geography in Hollenbeck. The northern position, labeled as Position 1 in Figure 5.6A, is comprised of the turf of 11 different gangs plus the unclaimed areas (which accounts for the presence of this position in some of the census block groups in the southern half of Hollenbeck). The southern position, labeled as Position 2 in Figure 5.6A, is comprised of the turf of 18 different gangs. This north-south gang geography corresponds to an observation in Tita et al. (2003) of a strong north-south division in the rivalry network based on a landscape feature: the San Bernadino Freeway (Interstate 10) bisects Hollenbeck and may constrain gang interaction in the same way that Tita et al. (2003) argues that built landscape and political boundary features do. Interestingly, CONCOR grouped the unclaimed areas of Hollenbeck together with the turf of the gangs in the northern half of Hollenbeck. This suggests two insights: 1) the spatiality of geographic embeddedness is mediating the rivalry links between gangs in Hollenbeck as the rivalries are clearly geographically organized at this level; and 2) that the material geography of violence in claimed turf in the north may be more similar to the patterns in the unclaimed areas than to the claimed turf in the southern position. While we return to the first point in the concluding discussion of the paper, the second point is easily evaluated using gang-related violence as a metric. The southern position in Hollenbeck clearly experienced more violence as the mean amount of gang violence in the southern

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position was over 30% higher (33.76%) than that in the north. The ANOVA tests clearly pick up on the fact that the differences between the variations in violence between the two positions were larger than the variations in violence among each position.

*Second Split*

The second application of CONCOR to the spatialized social network subdivided the first two categories, resulting in a total of four new differently structured categories as shown by Figure 5.6B. The northern position was partitioned into two new geographies which suggest a center-periphery arrangement: Position 1.1 describes a geography comprised of the turf of six different gangs that roughly occupy the center of the original northern position plus the unclaimed areas of Hollenbeck while Position 1.2 describes a geography of the turf of five gangs to both the east and west of the first new position. Interestingly, the CONCOR correlations identify the unclaimed areas as most similar to the gang turf in the center of the northern position (1.1) which might suggest lower violence levels than in the east/west position (1.2). The southern position was also partitioned, but a different geographic pattern was evident. This position was subdivided into two new north-south oriented geographies: Position 2.1 describes the northern-most geography and is comprised of the turf of 12 different gangs while Position 2.2 describes the southern-most geography of 6 gangs. The number of gangs in Position 2.1 is at least double that of any other position, suggesting the possibility of more violence.

Despite the identification of four distinctly structured geographies based on patterns of geographic embeddedness and network positionality, violence data for the four new positions suggests fewer material differences, at least between each of the sub-

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groups of Positions 1 and 2. Mean violence among the four positions was lowest in the northern 'periphery' group (Position 1.2, mean of 7.48) but at very similar levels in the northern 'core' group (Position 1.1, mean of 8.34) which contained the unclaimed areas. Mean violence counts were highest in the southern-most group (Position 2.1, mean of 13.78) while violence counts for the final group were slightly lower (Position 2.2, mean of 12.48). Despite different patterns of geographic embeddedness and network positionality, there were not significant material differences in violence patterns between these two pairs of geographies. We believe this is an important matter and return to discuss this in more detail in the conclusion.

*Third Split*

The third application of CONCOR to the spatialized rivalry relations again subdivided the previously identified positions into eight differently structured positions which are mapped in Figure 5.6C. At this stage the geographies are considerably more complex but we wish to highlight the following features. First, only at this stage does the CONCOR process identify the unclaimed areas as unique and separate position (Position 1.1.1 in Figure 5.6C), which is meaningful as it shows that these areas are indeed implicated in the relationships that constitute violence in Hollenbeck. Second, of the northern-most positions derived from Position 1 (Positions 1.1.1, 1.1.2, 1.2.1, and 1.2.2) the violence levels are similarly low except for the gang geography that essentially lies between those where violence is highest (Position 1.1.2, mean of 10.44). For example, Position 1.1.2, composed of the turf of 6 different gangs, lies roughly geographically between the all the gangs of the southern most positions and the gangs of Positions 1.2.1

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and 1.2.2 but also geographically between the turf of the three different gangs that comprise Position 1.2.2. This finding points to a new spatiality, that of geographical betweenness, which may be implicated in producing a higher level of violence. Lastly, of the southern-most positions (Positions 2.1.1, 2.1.2, 2.2.1, and 2.2.2) violence is also similar for three of the positions and noticeably higher for the other position. Position 2.2.1, composed of the turf of a single gang (Evr_grn; see Figure 5.4), experienced 32 incidents of gang-related violence, one of the highest census block group counts for the entire study area. This outcome may also be attributable to a relational betweenness, as while the gang's turf is not obviously geographically situated between many other gangs or positions as in the previous example, it is situated between two important gangs, (WF and KAM; see Figures 5.3 and 5.4) that both have rivalries with Evr_grn and with each other. This relational betweenness may play a significant role in producing a high level of violence. The ability of the technique to highlight new and previously unobserved spatialities is an important outcome that we expand upon in the paper's conclusion.


CONCLUSIONS

The spatialities of social relations among and between gangs in Hollenbeck undoubtedly have implications and manifestations that cannot be completely captured and interpreted by the hybrid spatial analytic and social analytic methods used here. For example, dynamism is not present in our data and, as such, our analysis presents a presumably unchanging rivalry network and associated turf map. Social relations are inherently dynamic and, although changes occur within existing structures, today's rivalries may in fact be tomorrow's alliances. Our approach does not prevent the

consideration of different network structures over time and disaggregating networks temporally (in additional to distributing them geographically) would be a positive step toward introducing dynamism in a way that we were not able to with this data. Further, our example was quite streamlined in that only rivalries and relative location in space were considered for network position. This limitation undoubtedly overlooks some factors in the production of gang violence and therefore is not a perfect example of an analysis of multiple spatialities.

Nonetheless, accepting multiple networks of relations as analytic inputs is a hallmark of the techniques we presented and including other kinds of relationships that would better reflect the concerns of the overlapping networks of Ettlinger (2003) or the multiple spatialities of Leitner et al. (2008) is certainly possible. Even when considering the limitations of our example, it is evident that using territoriality as a lens through which to focus upon the rivalry relations in Hollenbeck leads to several important conclusions. Although the specific findings of the gang rivalry networks in Hollenbeck are certainly dependent of the geographic and historical context of gangs in Hollenbeck, we interpret these findings in a way that emphasizes the utility of the demonstrated concepts and methods for other topics.

The specific findings of this study offer meaningful evidence that, in Hollenbeck, the overall geographic pattern of violence is interpretable by spatializing the rivalry relationships and that new spatialities can emerge from the complex web of relationships in geographic and network space. To the first point, the spatialized positional analysis clearly reveals that the rivalry network has produced distinct spatial patterns. These distinct geographies, easily verified by the material geography of gang-related violence,

are formed by the rivalry network but also clearly mediated by the relative location of each gang in geographic space. This geographic mediation of the rivalry network is more than just an argument of space as mechanism of integration of social processes (e.g., Goodchild et al. 2000) and one would be hard pressed to reach this observation through either a conventional spatial analysis that did not consider social relations or a conventional social network analysis that did not consider geography.

To the second point, social network analytic techniques can simplify complex and multidimensional network structures, which may also highlight new kinds of spatialities that emerge from the interplay of different spatialized networks. For example, spatialities of betweenness may be important to the overall geography of violence in Hollenbeck. We use betweenness here in its social network sense, as a kind of network centrality that has to do with being located between and connecting different actors in a network structure (Freeman 1977; Friedkin 1991). In the social network literature, the betweenness concept has typically been used to evaluate the importance of particular actors in gatekeeping roles (also known as 'brokerage') or to explain the benefits for actors that bring together otherwise disconnected networks ('structural holes'), both major themes in social network analysis when dealing with flows of information, capital, or anything else that can move through a network.[37] Our concept of spatialities of betweenness is related to these ideas in that being situated between other actors either in social space (relational betweenness), geographic space (geographical betweenness), or both may be important

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[37] Influential examples of these concepts related to betweenness in the social network literature include Granovetter's (1973) investigation of how information about job opportunities is transmitted in professional social networks and Burt's (1992) analysis of structural position on entrepreneurial success. Various methods to operationalize and evaluate measures of betweenness have also been developed, mostly inspired by the work of Freeman (1977; 1979). See also Wasserman and Faust (1994) and Everett and Borgatti (2005).

elements in understanding the overall geographic patterns of gang violence. Given that part of what is 'flowing' in our example of the territorialized network of rivalries is violence, betweenness is not necessarily a positive and bridging a structural hole (such as connecting different spatial domains) may mean being targeted for more violence.

Although the research presented in this paper concerns a specific kind of violence between specific kinds of social units in a specific locality, there are general implications for research into other contexts that are framed here in terms of methodology. First, and most importantly, the patterning of ties in the social network, or the structure of social relations, can and should be understood geographically. Despite arguments that geographic perspectives on social networks (especially while utilizing social network analytic methodologies) are difficult to achieve (Leedners 2002; Bosco 2006a), this paper demonstrates a relatively simple yet powerful technique to link relational networks with geography. Second, because many relations have a material geographic nature, positional analyses can yield insights into how social relations may be implicated in the production of differentiated spaces/places. These insights may be particularly valuable because they are arrived at in a novel fashion. By and large, investigations into spatiality in geography are almost exclusively qualitative affairs. In as much as the conventional approach to spatiality may not easily penetrate other social science disciplines where quantitative methodologies remain central, the addition of a quantitative and empirically-minded set of techniques that engages with issues of spatiality is significant.[38] Third and lastly, while the methods demonstrated in this paper are capable of standing alone, they seem particularly valuable when used in concert with other ways of knowing. As noted in the

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[38] See O'Loughlin (2000) for an example of how different methodologies contribute to keeping ideas from conventional political geography apart from the mainstream of thought and practice in political science.

discussion of specific findings about the spaces of gang rivalry in Hollenbeck, the analytic methods used in this paper answer some questions while suggesting others and are not offered as an absolute substitute for granular, situated, and ethnographic knowledge.

This paper focused on introducing a set of techniques that we feel can be compatible with issues in geography concerned with the patterning of social relations. However, because we focus on methodology here, we are not making an explicit argument about theories of social relations and, as such, the issues of precisely how territorially-defined gang rivalry networks produce different patterns of violence in Hollenbeck are not exhausted in our study. Many paths for future inquiry are open. Although not intended as a comprehensive list, we wish to use our example to draw attention to a few possibilities that we also feel suggest the flexibility and applicability of social network analysis methods and techniques to other kinds and scales of research in geography. As we have already mentioned, issues associated with changing patterns of relationships over time is a potentially fruitful line of inquiry. Beyond this, perhaps the most important frontier is the investigation of gang rivalries in other geographic contexts. Relational data on other gang rivalry networks at similar geographic scales would allow comparisons that may reveal 'domain specific laws' applicable to other contexts (e.g., O'Loughlin 2000) or suggest other kinds of relationships that should also be considered. Even if the focus remains with the gangs of Hollenbeck, network methods offer potential lines of inquiry.

Positional analyses, such as the type performed in this paper, are holistic and global in that they are concerned with the structural properties of an entire network.

However, they are also but one possible approach to applying social network analysis methods to issues of the social construction of space. For example, an 'egocentric' approach, which focuses on properties of the network from the perspective of different actors situated in particular locations, might tell a great deal more about the differences and similarities between places (social locations) while also refocusing inquiry from networks of gangs to networks of individuals.[39] It is our hope that through the example of Hollenbeck, the issues and methods presented in this study encourage future research into how social networks are involved in the social production of space and how social network analysis methods may be utilized to understand if and how the structure of social networks have implications for material geographic outcomes.

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[39] A focus on individuals is a persistent concern for geographers as a way to avoid spatial fetishism. Adapting these arguments to social networks, Ettlinger (2003, 146) argues that the unit of analysis (or node) in a network should be at least partly composed of individuals as a way to avoid "a reification of firms or other organizations or networks themselves." In our example, the units of analysis are both social collectives (gangs) and the spaces they control (turf). Although we feel that in our example the gangs themselves reify turf with their abiding emphasis on territorial control, we acknowledge the importance of Ettlinger's (2003) argument to certain research objectives and advocate careful consideration of her argument when selecting the unit(s) of analysis.

Table 5.1: Global Moran's *I* results of violence counts by census block (*n* = 120)

| | 1st order contiguous neighbors only | 1st and 2nd order contiguous neighbors |
|---|---|---|
| **Rook contiguity** | 0.09 | -0.09 |
| **Queen contiguity** | 0.08 | -0.04 |

Table 5.2: Analysis of variance results for each iteration of the CONCOR process

| | Position | No. of gangs | Mean no. of violent incidents | $n$ (block groups) | Parametric ANOVA ($F$) | Non-parametric ANOVA ($\chi 2$) |
|---|---|---|---|---|---|---|
| **1st Split** | **1** | 11[†] | 8.00 | 52 | 9.586[a]*** ($p = 0.002$) | 6.518[a]** ($p = 0.011$) |
| | **2** | 18 | 13.06 | 68 | | |
| **2nd Split** | **1.1** | 6[†] | 8.34 | 41 | 3.294[b]** ($p = 0.023$) | 7.595[*] ($p = 0.055$) |
| | **1.2** | 5 | 7.48 | 27 | | |
| | **2.1** | 12 | 12.48 | 29 | | |
| | **2.2** | 6 | 13.78 | 23 | | |
| **3rd Split** | **1.1.1** | 0[†] | 7.00 | 25 | 2.404[c]** ($p = 0.025$) | 11.738[c] ($p = 0.110$) |
| | **1.1.2** | 6 | 10.44 | 16 | | |
| | **1.2.1** | 2 | 6.00 | 4 | | |
| | **1.2.2** | 3 | 7.74 | 23 | | |
| | **2.1.1** | 6 | 14.30 | 10 | | |
| | **2.1.2** | 6 | 11.53 | 19 | | |
| | **2.2.1** | 1 | 32.00 | 1 | | |
| | **2.2.2** | 5 | 12.95 | 22 | | |

[†] includes unclaimed areas

[a] d.f. = 1, [b] d.f. = 3, [c] d.f. = 7

[*] $p < 0.1$, [**] $p < 0.05$, [***] $p < 0.01$

Figure 5.1: The Hollenbeck Policing Area is east of downtown Los Angeles. Numerous street gangs are active in Hollenbeck, but elements of the urban landscape, including the Los Angeles River and the Pasadena Freeway, serve to limit interactions with gangs from other areas.
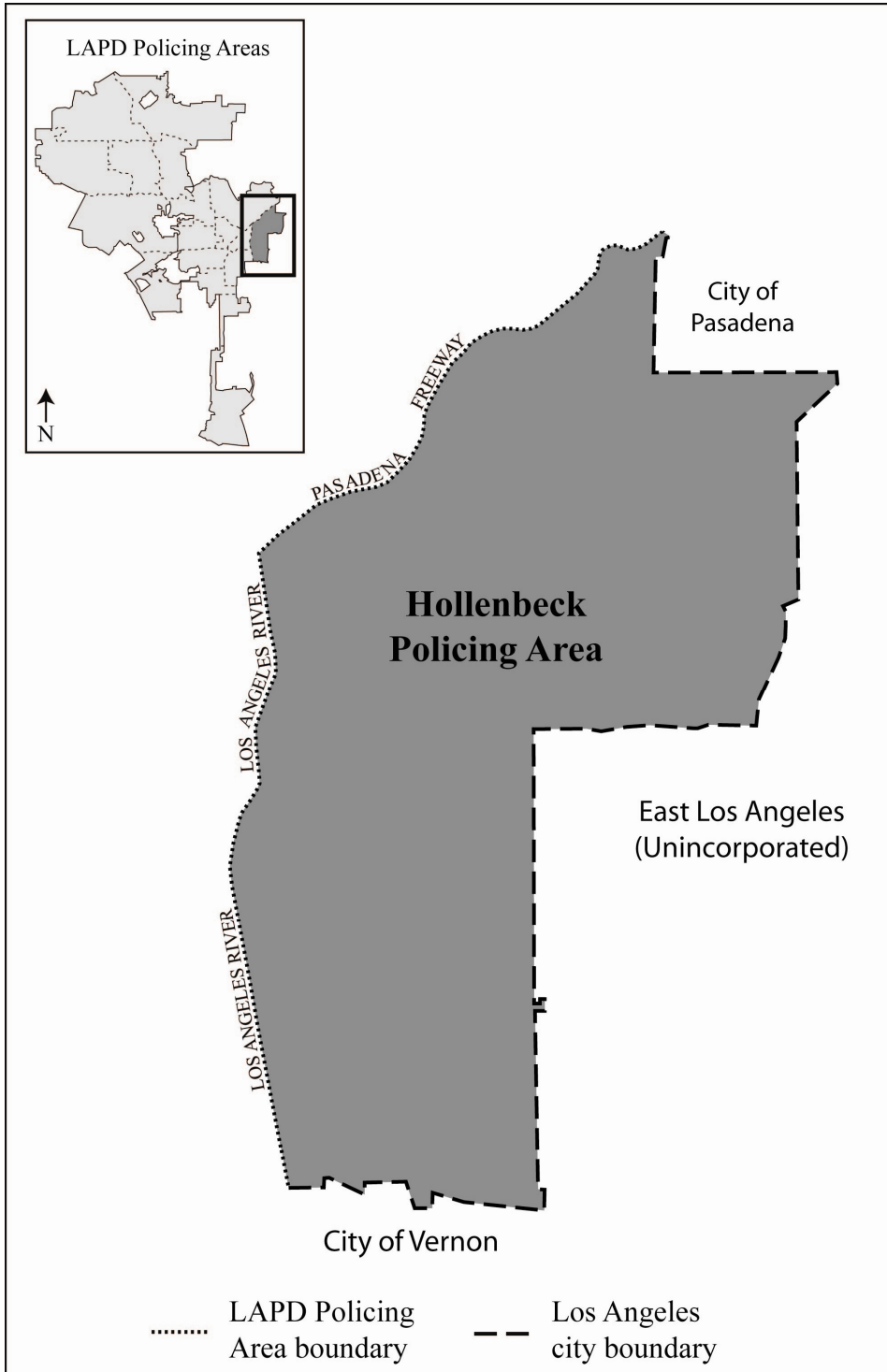
Figure 5.2: Gang and gang-related violence in Hollenbeck from May 2000 through December 2002 by U.S. Census block group



No. violent crimes
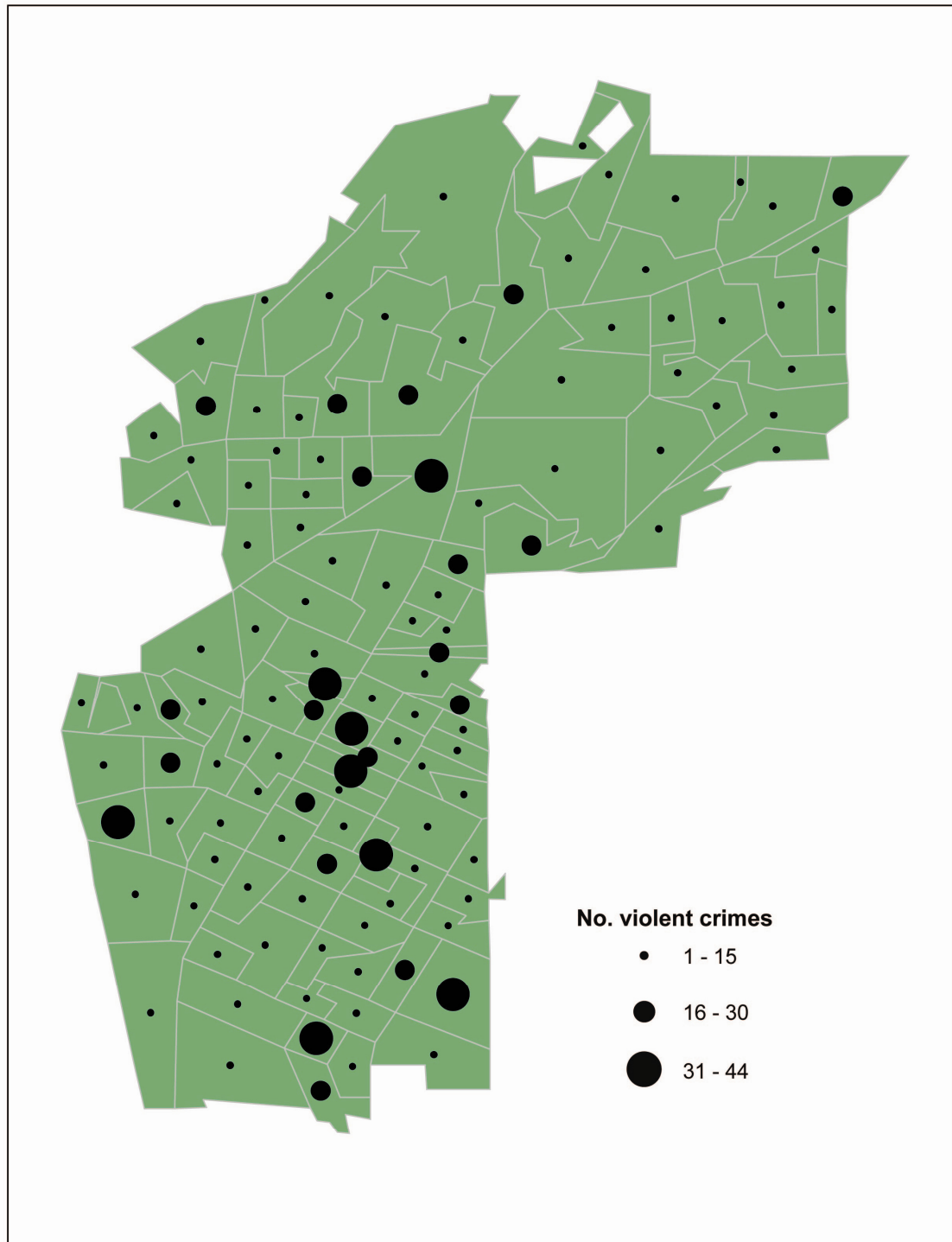
·    1 - 15

●    16 - 30

⬤    31 - 44

Figure 5.3: A network diagram of the rivalry network among gangs in Hollenbeck. Each of the 29 gangs is shown as a node and the presence of a rivalry between two gangs results in a link between them. Although all gangs are connected to the network by at least one rivalry, all but two gangs are involved in multiple rivalries.
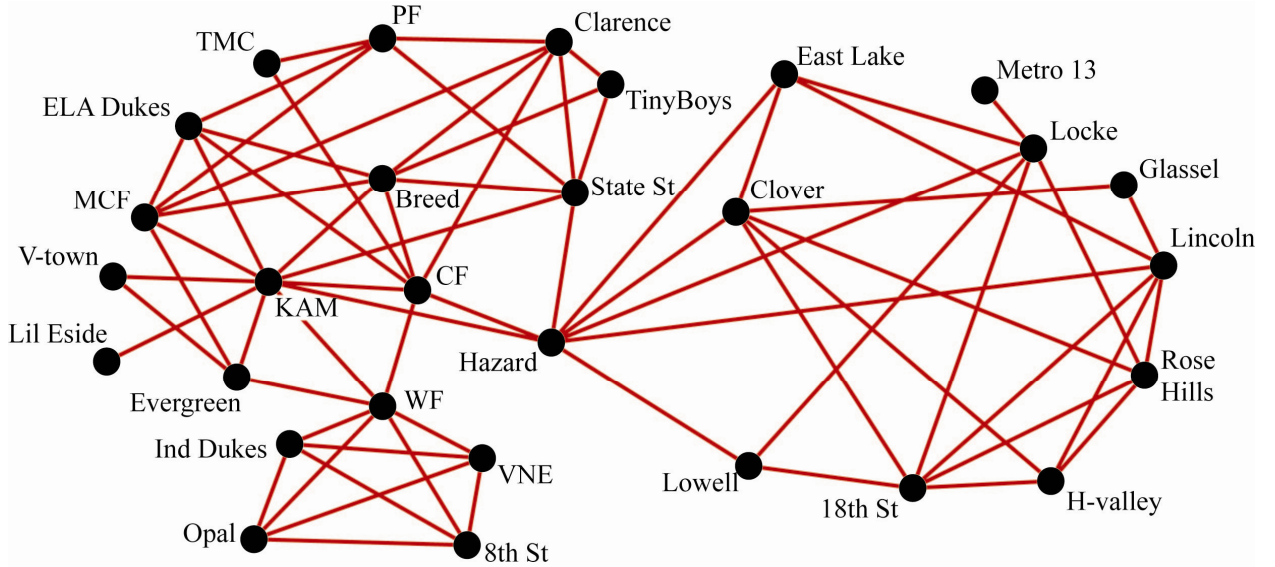
Figure 5.4: Placing the gang rivalry network (based on turf locations) into the geographic space of Hollenbeck shows both the complexity of the social relations and how some relations 'stretch' long distances to link gangs while others link only immediate neighbors.
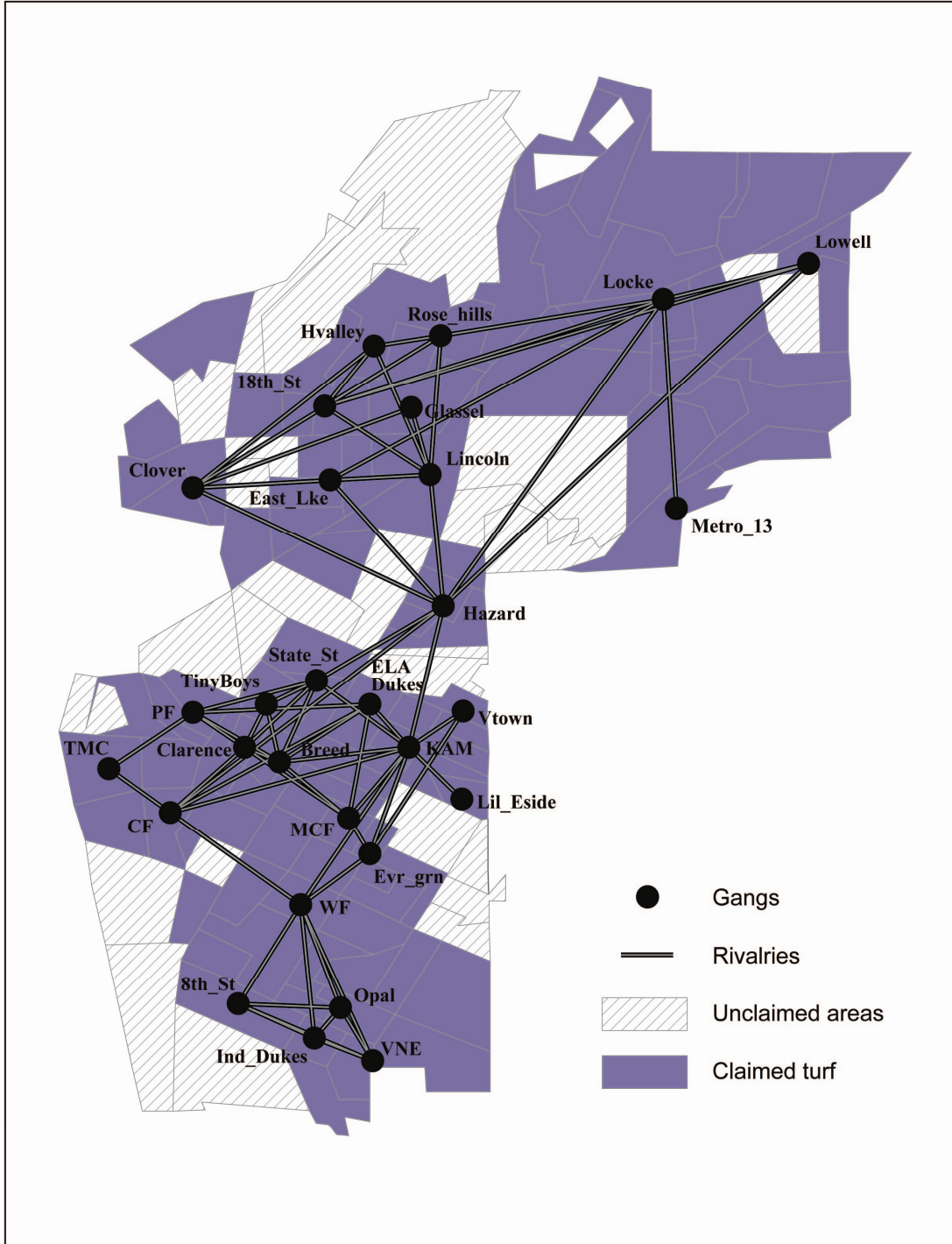
Figure 5.5: A dendrogram of the CONCOR positional analysis process through three splits. Each of the 30 units (29 gangs plus one unit for unclaimed turf) in Hollenbeck is classified into distinct positions at each stage of the process
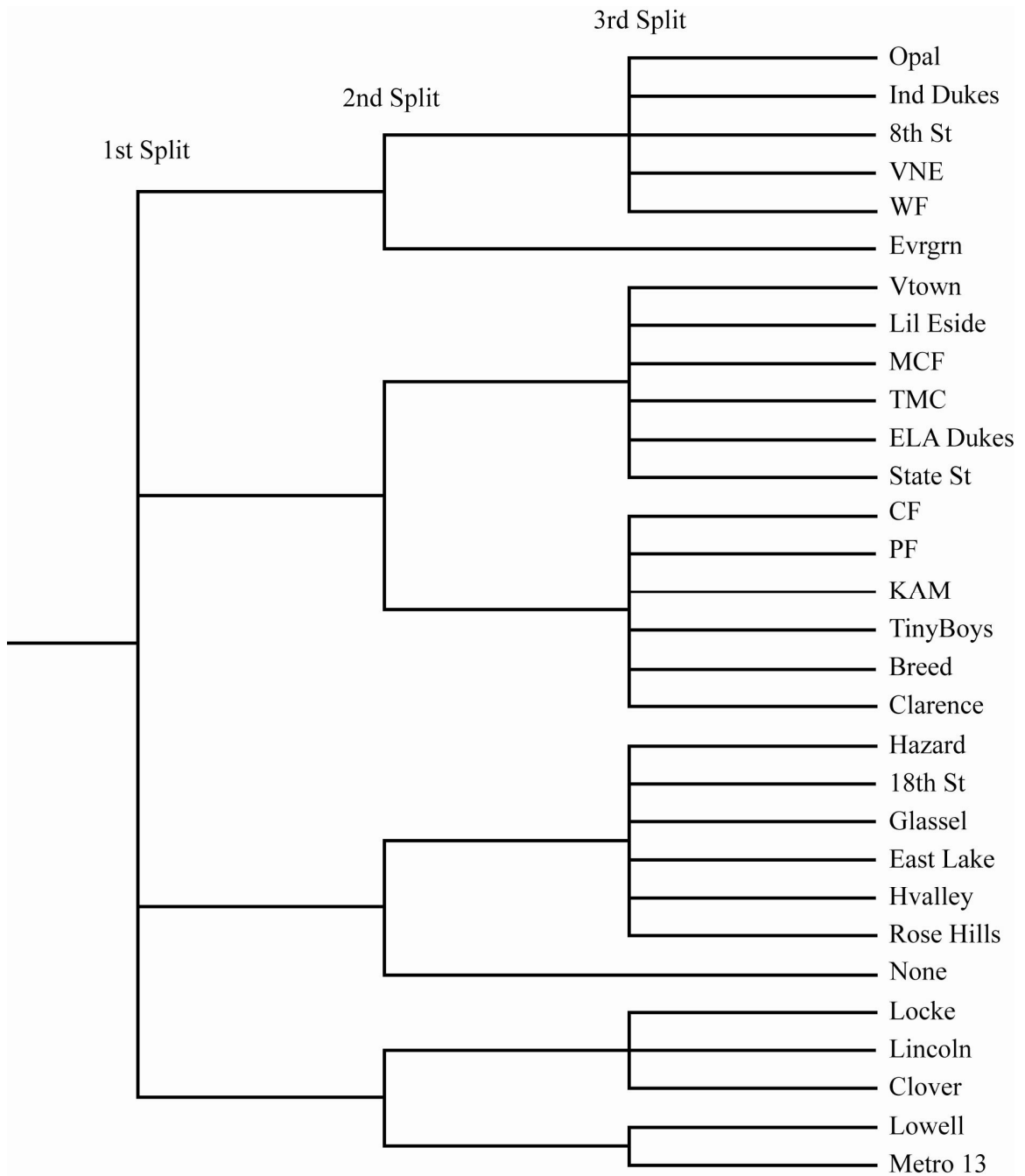
Figure 5.6A: The first split of the CONCOR process reveals two positions in the gang network, one in the north of Hollenbeck and one in the south.



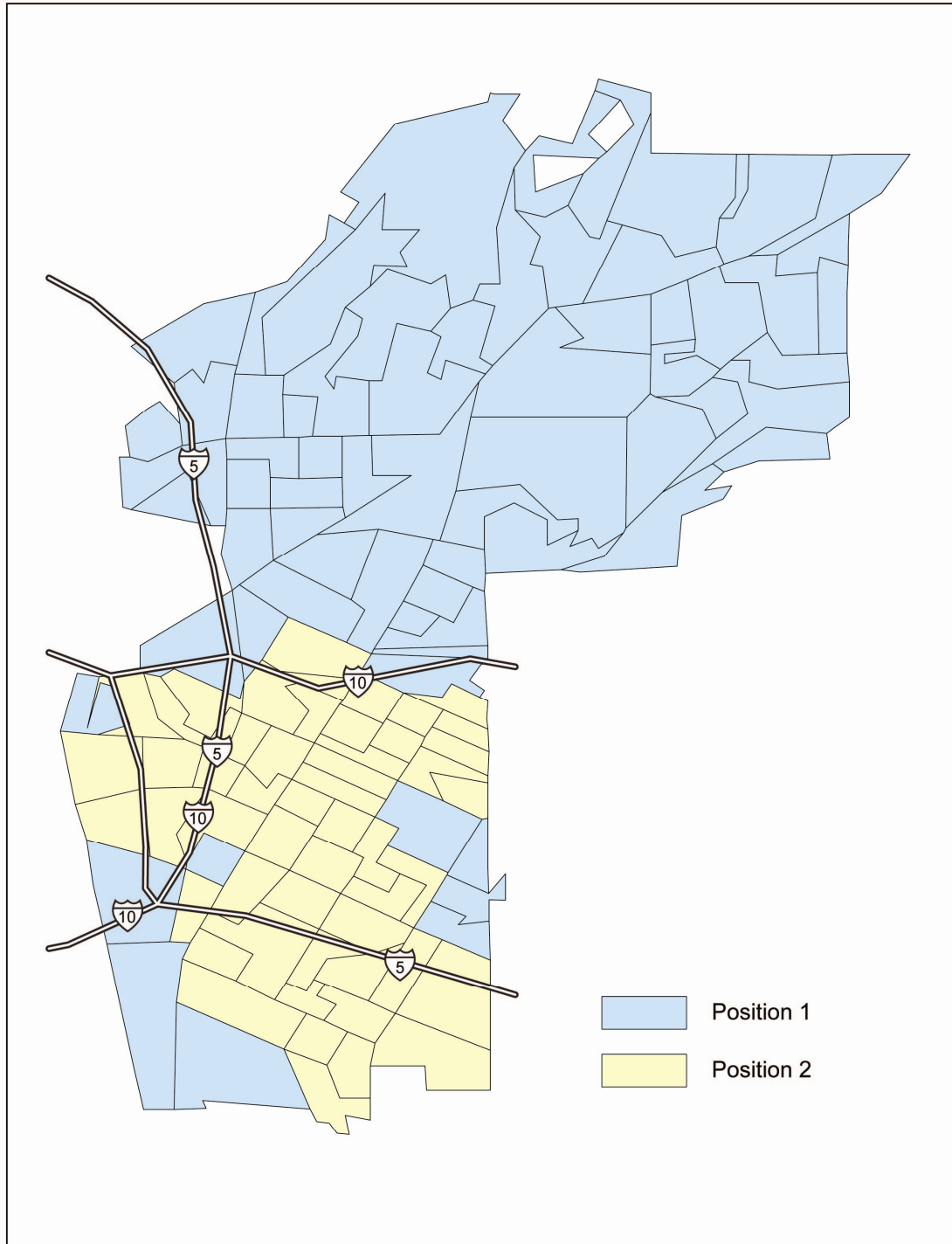Legend:
- Position 1
- Position 2

Figure 5.6B: The second split of the CONCOR process subdivides each of the first two positions.
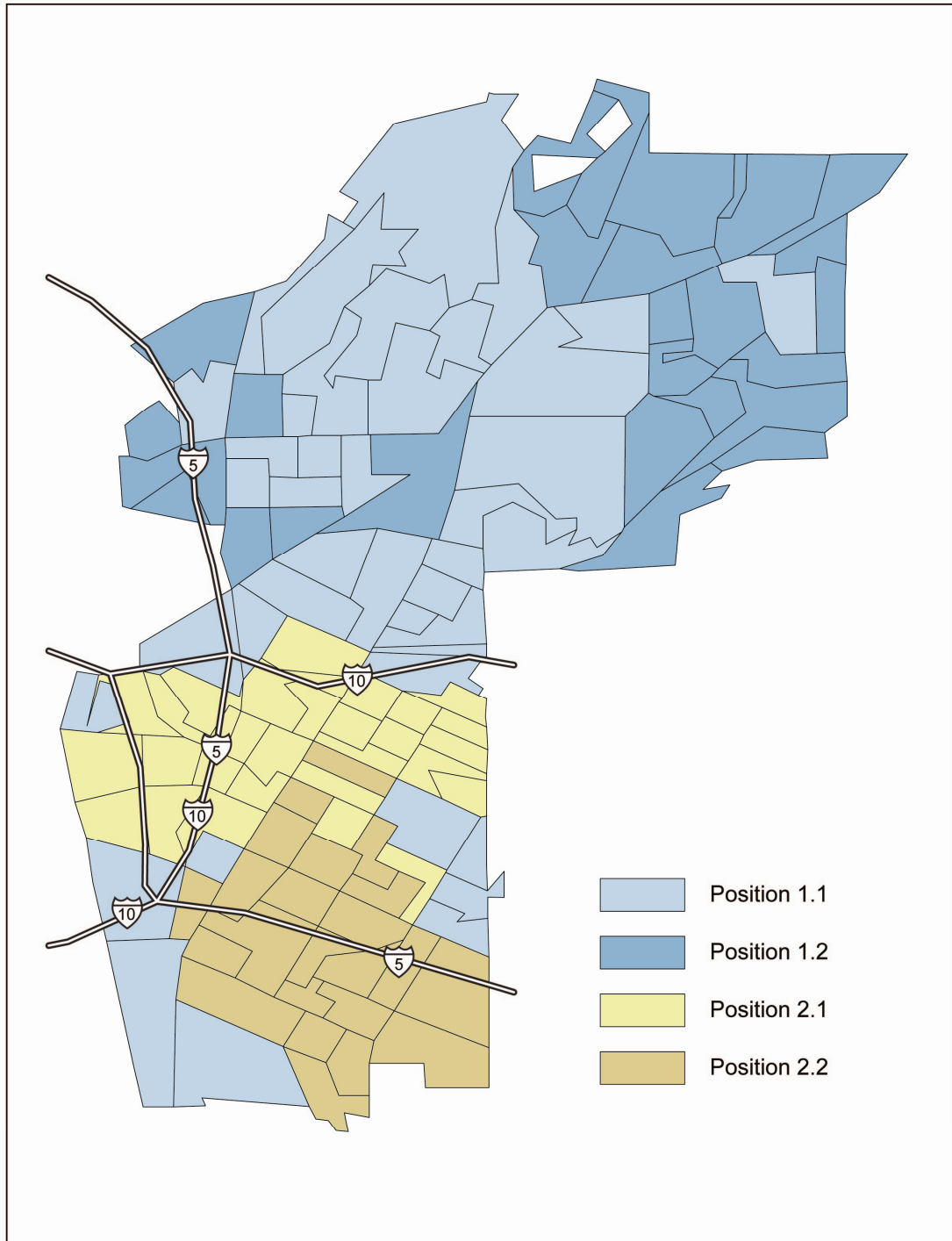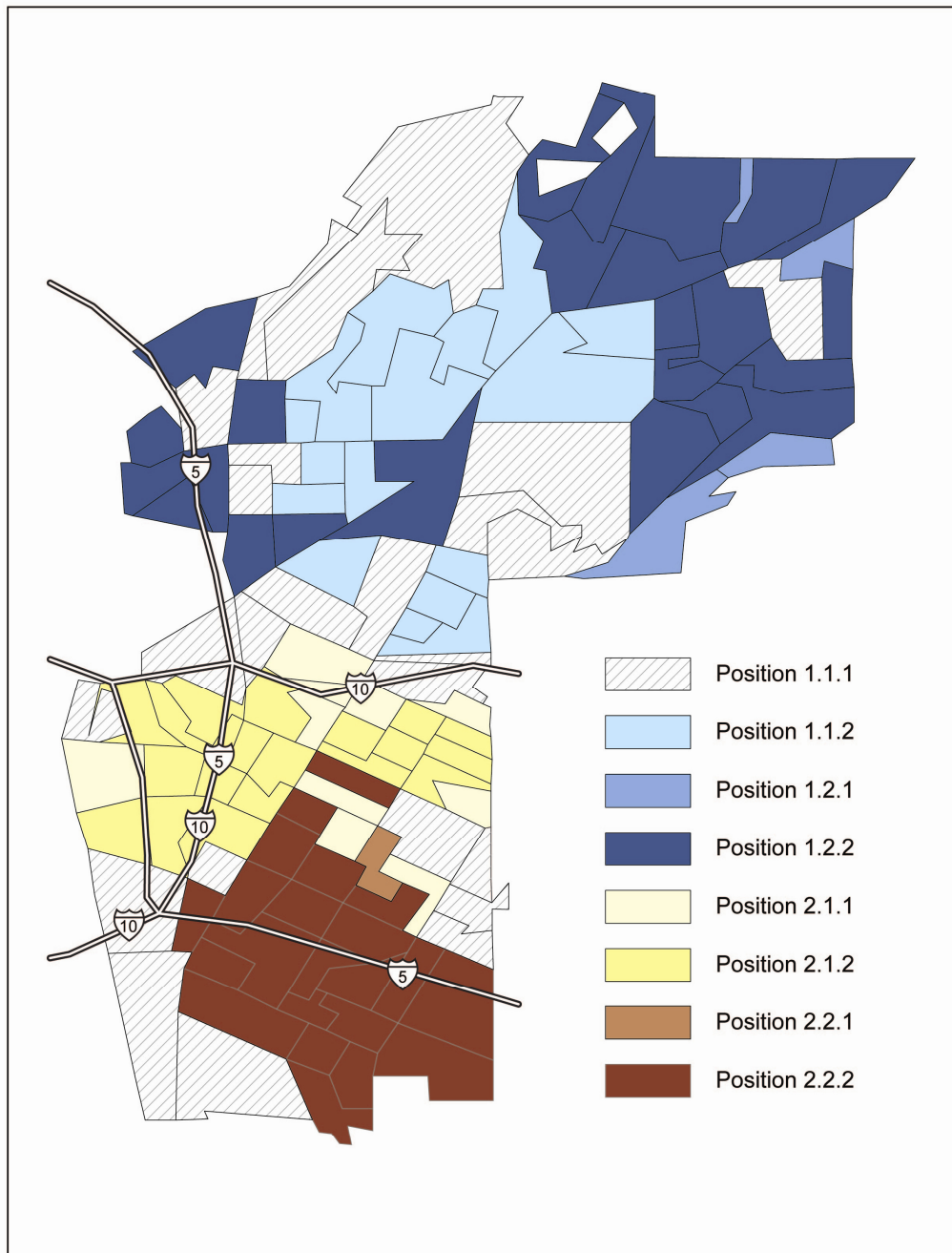
Figure 5.6C: The third split of the CONCOR process continues to subdivide positions. In both the north and south areas of Hollenbeck, core-periphery positions continue to be suggested.

# CHAPTER 6

## CONCLUSIONS

Quantitative spatial analyses of social behavior within criminology have progressed significantly within the last decade, but further advances have been limited by several factors, the most notable of which is a need for a more rigorous theoretical approach through which we can better understand the processes of gang-related violence. The research presented in this dissertation has attempted to contribute to this endeavor by focusing on the geography of gang violence within a single area of a city over a relatively short period of time. By integrating contemporary thinking in human geography about the social production of space and place with concepts and methods in social network analysis and spatial criminology, this study has presented an alternative framework to consider how the processes of competition, both territorial and non-territorial, contributed to the production of differentiated spaces of gang violence in east Los Angeles. In this chapter, I summarize the findings presented in the empirical chapters and discuss the importance of the framework developed for this research. I also discuss issues for future research that are also drawn from these conclusions.

DISCUSSION

As with many other social sciences, spatial regression has become an important way to understand and incorporate context in criminology. These models typically use spatially lagged variables as proxies for various social phenomena thought to be responsible for the consistent finding that spatial clustering of crime events remains even after controlling for place-to-place variations in compositional effects such as race,

ethnicity and poverty. These efforts are a positive first step but this research demonstrates that the way in which space is incorporated into such models requires careful consideration. Specifications of the spatial weights matrix that rely on spatial contiguity to define the spatial reach of the various social processes posited to be responsible for clustering forces researchers to assume that all such processes decay rapidly over geographic distance, and therefore matter only among spatially contiguous neighbors. Furthermore, even when multiple social processes are considered, the conventional modeling approach is to specify a single spatial weights matrix rather than specify different kinds of connections between places for different social processes. In addition to making it impossible to parse the impact of one process from that of another, this is an atheoretical approach to understanding why and how space matters.

Building on these perspectives, this research has demonstrated that "space" continues to matter as the compositional characteristics of places cannot adequately account for the overall geographic patterns of violence. The findings presented in this research also verify that gang rivalries are an important mechanism in the spatial distribution of gang-related violence. However, there is also evidence that the spatial reach of these rivalries extends well beyond simple contiguity even when considering different units of analysis, such as those defined by gang territorial boundaries, or at the smaller scale of census units. That is, gang rivalries play an important role in influencing levels of violence across the study area but the geographic scope of these rivalries is not limited to adjacent neighbors. By carefully considering the socio-spatial dimensions of gangs in terms of their territorial claims and the rivalry networks that connect them, it is possible to create a spatial weights matrix that explicitly captures the geographic

dimensions of the patterns of social influence among the gangs. The violence committed by, and against, gang members in a socially and geographically distinct area of Los Angeles is largely a function of a social process that spans the local geography in such a way that violence in non-contiguous areas impacts levels of violence in a focal neighborhood.

There are both practical and theoretical points that merit emphasis in the face of the above findings that have obvious implications for the application of spatial analysis in criminology. The practical point is that different specifications of the spatial weights matrix, or $W$, can impact modeling results statistically. The theoretical point is that the analyst must be prepared to engage the question of why and how space matters. This remains the most pressing issue for analysts: to consider how the selected specification of $W$ relates to one's theoretical framework about the phenomenon of interest. In the absence of a theoretically-grounded $W$ specification, one is invariably left with important and often unaddressed questions about the nature of the possible interactions. As there remains no statistical method capable of estimating the 'best fit' of a spatial weight matrix to one's data (Leenders 2002), embodying one's theory into the specification of $W$ is the only sensible recourse available.

As demonstrated in this research, grounding a model of spatial interaction in a theory of spatiality is possible. This was done by drawing on the understanding in geography of the importance of context to human activity and that social and spatial processes are bound up together. This is best demonstrated in the literature through the concept of "place," which is associated with "historical tradition, socio-cultural relations, context, and geo-sociological effects" (O'Loughlin 2000: 133). Given the importance of

territory (turf) and territorial control to the gangs of Hollenbeck, the specific socio-spatial processes were theorized as at least partly territorial in nature, which led to the development of a 'hybrid' $W$ that captured both territorial and non-territorial competitive interactions between the gangs. In this research, spatial interaction between the gangs in a particular place-based context was theorized and a $W$ that matched that theory as closely as possible was a strong predictor of the overall geography of gang-related violence. These findings demonstrate the value of employing such an approach. It is my hope that demonstrating an inductive approach to theorizing spatial interaction will encourage others to do the same.

Beyond demonstrating the potential for incorporating theory in spatial analysis is a perhaps more meaningful contribution by this research. By using the techniques and concepts of social network analysis, this research has offered meaningful evidence that new spatialities can emerge from complex web of social relationships in geographic and network space. More plainly, by theorizing, tracking, and spatializing social relationships, this research has shown that variations in the material geography of gang-related violence were partially formed by the geography of the rivalry network but also clearly mediated by the relative location of each gang in geographic space. This geographic mediation of the rivalry network is more than just an argument of space as a mechanism of integration of social processes (e.g., Goodchild et al. 2000). Furthermore, one would be hard pressed to reach this observation through either a conventional spatial analysis that did not consider social relations or a conventional social network analysis that did not consider geography.

A further contribution is made by demonstrating that social network analytic techniques can not just simplify complex and multidimensional socio-spatial network structures but also reveal new kinds of spatialities that emerge from the interplay of different networks of relationships. For example, because the rivalry relations between gangs at times stretch over relatively long distances and bypass territorial neighbors, the spatialities of betweenness appear to be meaningful in the neighborhoods of Hollenbeck. The spatiality of betweenness, or the notion that being situated between other actors either in social space (relational betweenness), geographic space (geographical betweenness), or both, is an important element in understanding the overall geographic patterns of gang violence and only is revealed as such by considering the interplay of different networks.

Although the research presented in this dissertation concerns a specific kind of violence between specific kinds of social units in a specific locality, there are general implications for research into other contexts. While I frame these issues here in terms of methodology, they are drawn from the overall point regarding the importance for theoretically information spatial analyses. First, and most importantly, the patterning of ties in the social network, or the structure of social relations, can and should be understood geographically. Despite arguments that geographic perspectives on social networks (especially while utilizing social network analytic methodologies) are difficult to achieve (Leedners 2002; Bosco 2006a), this research demonstrates relatively simple yet powerful techniques to link relational networks with geography. Second, because many relations have a material geographic nature, positional analyses can yield insights into how social relations may be implicated in the production of differentiated

spaces/places. These insights may be particularly valuable because they are arrived at in a novel fashion. By and large, investigations into spatiality in geography are almost exclusively qualitative affairs. In as much as the conventional approach to spatiality may not easily penetrate other social science disciplines where quantitative methodologies remain central, the addition of a quantitative and empirically-minded set of techniques that engages with issues of spatiality is significant. Third and lastly, while the methods demonstrated in this paper are capable of standing alone, they seem particularly valuable when used in concert with other ways of knowing. As noted in the discussion of specific findings about the spaces of gang rivalry in Hollenbeck, the analytic methods used in this paper answer some questions while suggesting others and are not offered as an absolute substitute for situated and ethnographic knowledge.

FUTURE RESEARCH

This research has focused on introducing a set of approaches and techniques that can be compatible with theoretical issues in geography concerned with the patterning of social relations. Although this dissertation has focused on a single issue (gang violence) in a single setting (the neighborhoods of Hollenbeck), many paths for future inquiry are open. I wish to draw attention to possibilities based on the particular limitations of this particular study as well as to those that I feel suggest the flexibility and applicability of social network analysis methods and techniques to other kinds and scales of research in geography.

From the point of view of this particular study, our findings are based on a series of operational choices (e.g., how to measure variables of interest, coding schemes, units

of analysis, etc.) that could be possibly improved upon. For example, the dependent variable in the empirical chapters was a count of violent crimes committed by or against gang members in the Hollenbeck Policing Area between May of 2000 through December of 2002. While this violence is therefore certainly "gang related" in that it involves gang members in some fashion, it is not entirely certain how much of the violence is "gang motivated" in nature (e.g., protection of turf from an incursion by rival members and suitable to model through the rivalry and turf-based territoriality networks) as opposed to opportunistic in nature (which may have little to do with either gang rivalries or turf claims). Further, as the dependent variable included different types of violent crimes (aggravated assaults, simple assaults, assault with a deadly weapon, attempted homicides, homicides, robberies, kidnappings, and firing a gun into an inhabited dwelling/vehicle), perhaps disaggregating robberies from assault/homicides sharpen the patterns under investigation in this study.

From the spatial analytic perspective, perhaps the most important improvement for future research lies not in further disaggregation of the dependent variable but of the study area itself. Based on the traditional emphasis on areally aggregated data in spatial criminology (the 'ecological' tradition), this study has used census units as the basic unit of analysis. However, given that the crime variable is already geographically disaggregated from any areal units (see Figure 4.3), one need not adopt existing areal units for this type of analysis. Recent efforts in different types of analytic human geography have emphasized the precise mapping of the location of the phenomenon of interest (e.g., O'Loughlin and Raleigh 2008) and by using GIS-based techniques to create new uniform units of analysis by overlaying a grid on the study site. This perspective has

the advantage of not privileging a particular type of areal unit and dealing with some of the issues of the MAUP problem. However, such an approach would likely preclude the use of social data aggregated into preexisting units (such as census units) and research using this approach remains a largely descriptive endeavor, emphasizing mapping, rates of diffusion, and statistical summaries (e.g., O'Loughlin and Raleigh 2008). A significant challenge for this perspective is to connect and evaluate the descriptive findings of spatial patterns to theories behavior of interest.

Future efforts should also attempt to incorporate dynamism and change over time. The data used in these studies was temporally pooled and as such, the analysis presents a presumably unchanging rivalry network and associated turf map. Social relations are inherently dynamic and, although changes occur within existing structures, today's rivalries may in fact be tomorrow's alliances. The approach presented in this dissertation does not prevent the consideration of different network structures over time and disaggregating networks temporally (in addition to distributing them geographically) would be a positive step toward introducing dynamism.

Further, this research was quite parsimonious in that only rivalries and relative location in space were considered as elements of socio-spatial network position. This limitation undoubtedly overlooks some factors in the production of gang violence and therefore is not a perfect example of an analysis of multiple spatialities. Nonetheless, accepting multiple networks of relations as analytic inputs is a hallmark of the techniques presented in this dissertation and including other kinds of relationships that would better reflect the concerns of overlapping networks (Ettlinger 2003) or multiple spatialities (Leitner et al. 2008) is certainly possible.

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Lastly, positional analyses, such as the type performed in this paper, are holistic and global in that they are concerned with the structural properties of an entire network. However, they are also but one possible approach to applying social network analysis methods to issues of the social construction of space. For example, an 'egocentric' approach, which focuses on properties of the network from the perspective of different actors situated in particular locations, might tell a great deal more about the differences and similarities between places (social locations) while also refocusing inquiry from networks of gangs to networks of individuals (e.g., Ettlinger 2003).

It is my hope that through the example of Hollenbeck, the issues and methods presented in this study encourage future research into how social networks are involved in the social production of space and how social network analysis methods may be utilized to understand if and how the structure of social networks have implications for material geographic outcomes. Even when considering the limitations of the example of gang violence in the neighborhoods of Hollenbeck, it is evident that letting geographically-informed theories of social behavior guide a spatial analysis can lead to meaningful insights. Although the specific findings of the gang rivalry networks in Hollenbeck are certainly dependent of the geographic and historical context of gangs in Hollenbeck, I believe this research has emphasized the utility of the demonstrated concepts and methods for other topics.

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