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Neighborhood co-offending networks, structural embeddedness, and violent crime in Chicago

Sara Bastomski[a,*], Noli Brazil[b], Andrew V. Papachristos[a]

[a] Department of Sociology, Yale University, PO Box 208265, New Haven, CT, 06520-8265, United States
[b] Spatial Sciences Institute, University of Southern California, 3616 Trousdale Parkway, Los Angeles, CA, 90089-0375, United States

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ABSTRACT

Neighborhood disparities in crime are a persistent feature of U.S. cities. Scholars have documented that both local structural conditions and characteristics of spatially proximate communities influence neighborhood crime rates. Previous studies on neighborhood inequality in crime, however, are limited by their focus on identifying average spillover effects between pairs of spatially contiguous neighborhoods, and have neglected to consider how the broader social organization of the city influences local outcomes. This study examines the role of neighborhood-level criminal networks in shaping the distribution of crime throughout cities. Employing arrest records and survey data from the Project on Human Development in Chicago Neighborhoods, we construct a neighborhood-level co-offending network for Chicago for 2001. We use this network to investigate how a focal neighborhood's homicide rate is influenced by its structural embeddedness within the larger inter-neighborhood co-offending network. Results indicate that a neighborhood's embeddedness increases the local homicide rate, even after controlling for the neighborhood's internal propensity toward crime and accounting for unobserved spatial processes.

1. Introduction

Scholars have characterized the urban landscape as an array of neighborhoods that function as interlocking and interdependent entities (Park and Burgess, 1925; Sampson, 2012). From this perspective, neighborhood spatial boundaries serve as meaningful, yet porous demarcations: local communities are connected to spatially and socially proximate neighborhoods in a discernable pattern of mutual influence (Peterson and Krivo, 2009). One unfortunate consequence of this interdependence, however, is that it may amplify neighborhood disparities in violent crime, as social ties linking residents of different neighborhoods may facilitate the spread of violence from one neighborhood to the next (Anselin et al., 2000; Kirk and Papachristos, 2011; Loftin, 1986; Morenoff et al., 2001; Peterson and Krivo, 2009; Tita and Greenbaum, 2009). Recently, research on the spatial diffusion of violence has benefited from increased attention to the significance of social networks in the diffusion process (Papachristos, 2011; Soller and Browning, 2014; Tita and Boessen, 2012).

Despite these recent advances, little empirical research interrogates a central assumption within the literature on neighborhood crime: that the interdependent nature of urban neighborhoods is largely uniform. This line of research typically addresses neighborhood interdependence using social or network lag models, and in doing so, emphasizes an average spillover effect between pairs of neighborhoods without explicitly investigating whether diffusion processes behave differently in various areas of the city or whether certain neighborhood conditions (such as segregation or gentrification) might exert an effect on such processes. We argue that by masking the extent of variation in the presence and strength of social ties between neighborhoods this previous approach is unnecessarily reductive.

The present study aims to uncover a higher order structure of inter-neighborhood social ties, and examines how this structure contributes to dramatic disparities in crime across the city of Chicago, IL. Drawing from recent work emphasizing that social ties may inhibit or promote crime (Browning et al., 2004; Kubrin and Wo, 2016), we investigate the role of deviant social ties in creating inter-neighborhood pathways that contribute to violence across the city. Employing a database of over 52,000 co-offending events, we construct an inter-neighborhood co-offending network that connects all neighborhoods in Chicago, and use a k-core decomposition to classify neighborhoods by their structural embeddedness within the network. Results from a series of network lag models

* Corresponding author.
E-mail addresses: sara.bastomski@yale.edu (S. Bastomski), nbrazil@usc.edu (N. Brazil), andrew.papachristos@yale.edu (A.V. Papachristos).

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indicate that a neighborhood's structural embeddedness is positively associated with rates of violent crime in subsequent years.

2. Social networks and neighborhood crime

2.1. Within- and between-neighborhood social ties, co-offending, and neighborhood crime

Neighborhood scholars have recently begun to note that "neighborhood effects" are in fact largely approximating the impact of spatially-bounded, local social networks (Hipp et al., 2012; Sampson, 2012). Specifically, social networks are thought to be a key intervening mechanism explaining the observed relationship between neighborhood features and local crime rates (Hipp and Boessen, 2013; Kubrin and Wo, 2016; Soller and Browning, 2014; Tita and Radil, 2011). For example, social cohesion between residents is thought to enhance trust, and improve a community's capacity to maintain informal social control (Sampson et al., 1997). Importantly, while social ties are typically construed in terms of inhibiting crime, such ties may also facilitate problematic behaviors (Browning et al., 2004; Patillo-McCoy, 1999). At a basic level, crime and deviance require information, skills, and logistical support, as well as deviant social norms that support such behavior. For example, social learning theory suggests that social ties—especially among peers—facilitate the acquisition of such resources (McGloin and Nguyen, 2013; Sutherland, 1937). Likewise, research on street gangs suggests that internal processes directly related to social ties among members—such as cohesion or loyalty—facilitate a range of group and individual deviance and criminal behavior (Hughes, 2013; Short and Strodtbeck, 1965).

Our study draws attention to a type of social tie that is particularly conducive to facilitating the exchange of such criminogenic resources: *co-offending*, when two or more individuals engage in a delinquent or criminal act together. Employing co-offending network data presents several strategic advantages. First, criminological work has established that co-offending acts account for a substantial proportion of all crime (Carrington, 2009; Felson, 2003; McGloin and Piquero, 2010; McGloin and Stickle, 2011), and has shown that co-offending relationships are integral to our understanding of social or group processes that contribute to crime (McGloin and Nguyen, 2013). Second, co-offending ties serve as a direct measure of the pathways by which criminogenic social influence flows. As such, we argue that co-offending is a behavior that demonstrates that criminogenic influence has been successfully transmitted from one person to another; alternatively, it is a direct measure of how social capital enables crime.

Though much of the empirical work on neighborhood effects focuses on how social interaction plays out within a given community, the modern city is not characterized by exclusively local ties but rather by "spatially unbounded" ties, i.e. connections between geographically distant people and communities (Mears and Bhati, 2006: 512; Wellman, 1999). Previous research suggests that social ties between spatially distant neighborhoods are generated via institutions, such as schools or community organizations, that provide a shared social context (Sampson, 2012; Schaefer, 2012). For example, gang involvement (Tita and Radil, 2011), and homophily in neighborhood-level socioeconomic indicators are thought to contribute to such ties (Mears and Bhati, 2006; Schaefer, 2012).[1] In much the same way, we assert that co-offending ties can breach community spatial boundaries, expanding the geographic reach of peer influence. Importantly, such processes do not operate solely at an individual level. There are numerous ways in which inter-neighborhood co-offending ties could impact aggregate crime rates. For example, inter-neighborhood ties may draw offenders to previously unknown territories, making it more likely that they will converge in time and space with potential co-offenders or targets in a new area of the city (Cohen and Felson, 1979; Schaefer, 2012). Additionally, criminal behavior is subject to social contagion (Morenoff et al., 2001), and at the aggregate level, travels between places in a manner that is not unlike disease vectors (Zeoli et al., 2014; Papachristos, 2011). Inter-neighborhood co-offending ties provide an explanation for this observed phenomenon: offenders might obtain skills or material resources from accomplices away from home, but then bring those criminogenic resources back to their home neighborhoods. Moreover, personal relationships create opportunities for conflict that could escalate into violence. For example, gang feuds are known to lead to retaliatory violence that crosses neighborhood boundaries (Papachristos, 2009; Papachristos et al., 2013). If these mechanisms function as expected, then the spatial location of inter-neighborhood co-offending ties could be used to systematically predict where these new outbreaks of crime could emerge.[2]

Recent work provides empirical support for the hypothesis that inter-neighborhood social ties are consequential for crime; scholars have even identified specific diffusion patterns that can only be explained by incorporating social network data into analyses (Papachristos et al., 2013; Tita and Greenbaum, 2009; Tita and Radil, 2011). These studies, however, have been limited to gang violence. As such, we know little about how deviant inter-neighborhood ties impact the broader population of crime events[3]; and even less about how the structure of such ties influences the diffusion of crime.

2.2. Multidimensional neighborhood interdependence

Though this recent work on gangs illuminates how violence diffuses between a given pair of socially connected neighborhoods, it fails to adequately capture how pairs of neighborhoods are nested within a larger "network of neighborhoods" (Sampson, 2012) or how the diffusion of crime might be related to social ties outside of the gang context. To our knowledge, only one previous study has investigated the relationship between the structure of inter-neighborhood networks and local crime (Hipp et al., 2013). Hipp et al. (2013) used simulated social network data to demonstrate that inter-neighborhood ties are largely associated with reduced levels of neighborhood crime. Continuing this line of inquiry, we argue that social ties between neighborhoods –whether they are deviant or pro-social—do not exist in isolation, and ought to be examined in relation to the broader social organization of the city (Granovetter, 1973; White, 1983). Studies using various network data, ranging from trade to adolescent friendship networks, have shown that node- and dyad-level outcomes are influenced by the

[1] In another manuscript (under review), we use exponential random graph models to examine the formation of inter-neighborhood co-offending ties in Chicago. We demonstrate that inter-neighborhood ties are more likely to form between dyads that are similar on socioeconomic indicators like concentrated disadvantage, even after adjusting for the spatial distance between neighborhoods.

[2] Importantly, we have good reason to expect that such inter-neighborhood ties are robust to the entry and exit of individual offenders within the network, as research shows that inter-neighborhoods ties form between places that are socially similar (Schaefer, 2012). Thus, as long as there are neighborhoods that are homophilous on important socioeconomic indicators, we might anticipate that inter-neighborhood ties are continuously regenerating. In this light, inter-neighborhood ties should be conceptualized as a structural component of the city, i.e., one that is comprised of micro-interactions, and yet distinct from them. This is analogous to emergent community traits, such as collective efficacy, that arise at the neighborhood level (Sampson et al., 1997).

[3] Schaefer (2012) examined the formation of inter-neighborhood delinquent ties in Maricopa County, Arizona; however, this study did not examine the subsequent impact on crime.

structural properties of the network in which they are embedded (Aronow et al., 2015; Haynie, 2001; Mani and Moody, 2014; Morris et al., 2009). In much the same way, we anticipate that there are several ways that the city-wide structure of inter-neighborhood ties could alter the dynamics of influence between pairs of neighborhoods.

First, a neighborhood that has many direct co-offending connections to other neighborhoods (i.e. high degree centrality) may be subjected to cumulative effects of multiple exposures to risky behaviors or influences. For example, if illegal guns are constantly being routed to a neighborhood via numerous inter-neighborhood pathways (Cook et al., 1995), this could impact aggregate rates of violence more quickly than if just a few pathways are available. Second, a neighborhood with many indirect ties is likely to be more exposed to the network's contents than one that is more peripherally positioned. For instance, a surge of violence in a neighborhood two degrees removed could impact a focal neighborhood-node via an intermediary neighborhood.

Third, if a focal node's network neighbors are highly connected amongst themselves, this subgroup is more resistant to disruption (Gross and Martin, 1952). In an urban context, we might imagine that an inter-neighborhood co-offending pathway could be weakened or entirely blocked by various barriers. Such barriers might include changes to transportation infrastructure, or increased police presence; over longer periods of time, demographic shifts due to labor market fluctuations, gentrification, or immigration could also disrupt social connection across neighborhoods. In any case, relationships between highly embedded neighborhoods would be less disturbed by such barriers: information and other resources could simply route through any number of alternate pathways within the network. At the same time, embeddedness is likely to strengthen relationships between dyads in a city-wide network by increasing the volume of resources that flow along these pathways, and also by reinforcing or amplifying any signal that is sent along them (White and Harary, 2001). Similarly, while a single offender may have limited influence on the behavior of other neighborhood residents, if numerous offenders are connecting with other criminals throughout the city, and then returning home to a given neighborhood, then this focal community is repeatedly exposed to criminogenic influences. Moreover, in a highly embedded community, an offender is likely to travel to other neighborhoods that are similarly exposed to criminogenic resources or influences in a consistent manner– meaning that within a given city, information or social norms could circulate intensely within a subgroup of highly embedded neighborhoods, but flow more weakly among less embedded neighborhoods. Thus, over time, given a durable inter-neighborhood network, embeddedness should have an observable impact on aggregate crime rates.

3. Current study

We depart from much of the previous work on social ties and neighborhood crime, by explicitly examining the deviant social ties that connect neighborhoods to a citywide criminal network. Specifically, we leverage a database of all known incidents of co-offending that took place in Chicago during 2001, and construct a neighborhood-level co-offending network – i.e., the network created by the co-offending of residents living in different neighborhoods throughout the city. As such, neighborhood-nodes (not individual offenders) are the main units of analysis. We conceptualize this network as a structural component of the city, one that is invisible without precise network data.[4] These ties could function as the social arteries of the city, at least as they pertain to crime.

3.1. Structural embeddedness

We foreground the role of neighborhood structural embeddedness in this inter-neighborhood co-offending network. By *structural embeddedness*, we refer to the multidimensional manner in which any single neighborhood is situated within a larger network of inter-neighborhood ties (Moody and White, 2003). Our approach draws from well-established measures used to detect socially cohesive sub-communities within a larger network: graph and node coreness (Seidman, 1983; Batagelj and Zaversnik, 2011). Structural embeddedness[5] at the nodal level captures numerous overlapping pathways of influence, three of which we draw attention to here: (1) the number of direct connections (i.e. degree centrality); (2) indirect or second-degree connections; and (3) the extent to which a focal node's network neighbors are connected amongst themselves. We anticipate that the power of any single network tie is dependent upon the broader structure of the network: dyads nested within the most insular communities of nodes will likely have stronger mutual influence (Granovetter, 1973; White and Harary, 2001). We maintain that it is crucial to uncover macro-level social structures that organize the city into sub-communities of neighborhoods linked via social ties: macro-level patterns may promote repeated social interactions and the spread of information, social norms, and other resources that could promote behaviors like criminal offending.

This approach is strategic. In contrast to many network community detection algorithms, which assign nodes to a single network community, the measure of embeddedness used here accounts for the nested nature of social communities. Thus, an embeddedness approach allows a neighborhood-node to be a member of multiple communities, with stronger ties to some communities as compared to others. Notably, by classifying neighborhoods in this manner, we present a new approach for characterizing the diverse social landscapes that organize the city of Chicago. Specifically, while inequality in neighborhood-level crime is well documented (see Sampson et al., 2002 and those cited above), we anticipate that observed differences in neighborhood crime at any point in time are an incomplete measure of inequality, and that the mechanics underlying this persistent inequality are partially determined by a deeply rooted social structure only visible with network data. Put differently, if we are concerned with how the social organization of a city advantages some residents while disadvantaging others, we ought to not only consider how living in a crime-prone neighborhood impacts one's life chances, but also how residing in a disadvantaged neighborhood may actually expose residents to an entire *class* of neighborhoods that are disadvantaged. Similarly, we might imagine that residents of advantaged neighborhoods are insulated from crime by being nested within a larger class of advantaged neighborhoods. This could partially account for dramatic community-level disparities in urban crime observed in the

[4] It would be a mistake to conceive of these inter-neighborhood ties as merely personal or otherwise temporary pathways, as the city-wide structure of the network remains stable even as individuals enter and exit. Though the stability of the network is not the focus of this paper, note that Charette and Papachristos (2017) have tested this assumption empirically. Specifically, they show that the structure of the inter-neighborhood co-offending is very stable between 1999 and 2004, and is robust to individual offenders entering and exiting the network. Thus, the 2001 network we present here is representative of longer term trends.

[5] We use the term "structural embeddedness" to refer to a node-level measure, i.e. node coreness (Batagelj and Zaversnik, 2011). This limits confusion caused by using the term "coreness," which can refer to either a graph-level or node-level attribute. For details, see Data and Methods section below.

U.S. With this in mind, we examine how structural embeddedness impacts the distribution of crime across Chicago.

Furthermore, while we expect that inter-neighborhood co-offending ties facilitate the flow of information and instrumental support between neighborhoods, we do not expect them to be impactful at an aggregate level until they reach a particular threshold (Granovetter and Soong, 1983). Deviant social norms that promote criminal offending are likely to require a certain level of social saturation, especially if they are competing with more conventional local social norms that penalize crime. This is in line with Coleman's (1961) concept of network closure. Thus, a high level of structural embeddedness within the co-offending network should more successfully influence behavior in a manner that impacts aggregate rates of behavior. As such, we expect that once a threshold is breached, embeddedness will have a measurable positive influence on neighborhood crime rates.

4. Data and methods

4.1. Data

Data for this project were obtained from three primary sources: the Project on Human Development in Chicago Neighborhoods (PHDCN), the Chicago Police Department (CPD), and the U.S. Census. The PHDCN is a major, interdisciplinary study that focuses on human development in neighborhood context in Chicago, including detailed survey data on 6,000 youth and their primary caregivers (Earls et al., 1997). The unit of analysis for this study is the neighborhood, which we operationalized by using 342 "neighborhood clusters" developed by PHDCN researchers (Earls et al., 1997).[6] PHDCN researchers designed these neighborhood clusters by joining the 847 Chicago census tracts such that each is internally homogenous on important indicators like housing density and racial/ethnic makeup. Additionally, neighborhood clusters were constructed to reflect important physical features of the city, such as highways, as well as how locals perceive neighborhood boundaries. Each neighborhood cluster consists of approximately 8,000 residents on average.

We employed CPD[7] incident-level arrest data from a single year (2001)[8] to construct a neighborhood-level co-offending network, which we describe in detail below. These data included information on offenders' demographic attributes, home addresses, and arrest locations. Additionally, we used point-level homicide data to construct the homicide rates that we use as the dependent variable as well as control variables in our main analyses (described below). Summary statistics for all neighborhood-level measures are reported in Table 1 below.[9] In contrast to previous work that used gang social network data to model diffusion (Papachristos et al., 2013; Tita and Radil, 2011), we used the *entire* population of co-offending relationships in Chicago. This ensures that we do not draw our criminal network boundaries too narrowly; this is an important consideration given that the typical co-offending relationship is characterized by a weak tie, since the modal co-offending relationship lasts for just one co-offending event (McGloin and Nguyen, 2013).

4.2. Constructing the neighborhood-level criminal network

To understand how patterns of co-offending link Chicago neighborhoods, we must first create a person-level co-offending network (who offends with whom) and then locate individuals within their respective neighborhoods of residence. To this end, we constructed a co-offending network using arrest data from the Chicago Police Department, where nodes represent unique individuals arrested by the police during this time period and each edge connecting the nodes represents an instance of co-offending.[10] In total, there were 230,791 arrests made in Chicago in 2001. Approximately 22.7 percent, or 52,414 cases, involved a co-offender and met our inclusion criteria (i.e., offenders lived in Chicago at the time of the arrest). Here, the average number of co-offenders per event was 2.84 and the modal co-offending event involved 2 offenders (by definition, the minimum number of co-offenders per event was 2, and maximum was 20). Each neighborhood-to-neighborhood tie represents 2.8 co-offending pairs on average. The minimum and maximum number of pairs per inter-neighborhood tie are 1 and 93, respectively.

After identifying each of the unique offenders, we then geocoded offenders' reported home addresses to one of 342 PHDCN neighborhood clusters. We established the co-offending connections between neighborhoods through a two-step process, which converted a two-mode neighborhood-by-arrest matrix into a one-mode neighborhood-by-neighborhood matrix—a common procedure when studying two-mode data in social network analysis (Watts, 2004: 248). First, we created the entire two-mode neighborhood-by-arrest event matrix in which each cell indicates the number of offenders from neighborhood i who were arrested in event j. To get the neighborhood-by-neighborhood matrix, we then multiplied the neighborhood-by-arrest matrix by its transpose; the result is a symmetric, neighborhood-by-neighborhood matrix in which each cell indicates the number of offenders living in neighborhood i who were arrested with offenders living in neighborhood j. We describe the properties and spatial layout of the resulting network in the Results section below.

4.3. Variables

4.3.1. Dependent variable

Drawing from restricted CPD arrest data, we constructed neighborhood homicide rates for 2002. To determine population per neighborhood for 2002, we used a linear interpolation of the population counts from 2000 and 2010 census data. Additionally, since homicide is a rare event and there is concern about measurement error, we used an empirical Bayes rates smoothing technique. Using

[6] The PHDCN provides data on 343 neighborhood clusters, including one that represents Chicago O'Hare Airport. We excluded the Airport neighborhood cluster, as it is not primarily a residential neighborhood (this decision is in line with other studies that used these data; for example, see Papachristos et al., 2011: 221).

[7] Data were provided by CPD's Division of Research and Development. Findings from these data in no way represent the views of CPD or the City of Chicago.

[8] Again, although we limited the network to a single year here, we have examined Chicago co-offending networks for 1999–2004 in another manuscript (under review), and found that the networks are very stable during that six- year time period . Using a larger time frame to define the network is problematic because the resulting network is so dense that it limits our ability to illustrate important variation within the network. Finally, note that we used networks from other years in robustness tests, described in detail below and in the Appendix.

[9] Table 1 also includes network descriptive statistics. We constructed two nearly identical inter-neighborhood co-offending networks: one in which inter-neighborhood ties were defined by having one or more pairs of co-offending ties (we have termed this the '1-pair' network), and a second where ties were having at least five defined by the presence of at least five pairs of co-offenders (a '5-pair' network). We discuss the construction of the 1-pair network directly below, and we discuss the 5-pair network in detail on page 14. We have included descriptive statistics for both networks in Table 1.

[10] We thank an anonymous reviewer for noting that inter-neighborhood co-offending networks could be constructed in at least two alternate ways: (a) linking neighborhoods if the same offender commits a crime in both places and (b) a source-destination network; where neighborhoods are linked if an offender lives in one place and commits a crime in another. In this study, we have followed the precedent set by Schaefer (2012), and prioritize pathways that form between offenders' residential neighborhoods. See Papachristos et al. (2014), and Schaefer (2012) for additional information on the creation of such co-offending networks.

Table 1
Neighborhood-Network Descriptive Statistics (N = 342[a]).

	Mean	Std. Dev.	Min.	Max.
Dependent Variable				
Log EB Homicide Rate, 2002	−8.58	0.74	−10.41	−6.97
Independent Variables				
Network Measures				
1-pair[b]				
K-core Embeddedness, 2001	40.49	10.65	7	50
Degree, 2001	70.98	34.77	7	179
Inter-to-Intra Neighborhood Ties Ratio, 2001	1.09	0.92	0.17	6.84
5-pair[c]				
K-core Embeddedness, 2001	9.94	3.21	0	13
Degree, 2001	17.78	11.77	0	63
Inter-to-Intra Neighborhood Ties Ratio, 2001	0.78	0.86	0	6.41
Structural Measures				
Log EB Homicide Rate, 2001	−8.63	0.78	−10.49	−6.78
Concentrated Disadvantage, 2000	0.00	0.91	−1.19	3.56
Immigrant Concentration, 2000	0.00	0.94	−0.98	2.45
Residential Stability, 2000	0.00	0.87	−1.97	2.06
Collective Efficacy, 1994-95	3.89	0.34	3.01	4.92
Population Size, 2001	8,381	3,504	965	29,800
Arrest Rate, 2001	0.09	0.10	0.003	0.80

[a]We exclude the Chicago O'Hare Airport neighborhood cluster.
[b]Network based on neighborhoods linked by 1 or more co-offending ties.
[c]Network based on neighborhoods linked by 5 or more co-offending ties.

this transformation, raw rates were adjusted using the city-wide grand mean; neighborhoods with smaller populations and larger variance received the largest adjustments (Bailey and Gattrell, 1995). The distribution of homicide rates remained dramatically skewed to the right, even after this transformation, so we used the log transformed homicide rate in our analyses. We used the same procedure to construct the 2001 homicide rate that is used as a control variable.

4.3.2. Independent variables

Our main independent variable is *structural embeddedness,* which we operationalized by employing a network measure used to detect socially cohesive sub-communities within a larger network: k-core (Seidman, 1983; Batagelj and Zaversnik, 2011). The k-core of a graph is the "maximal subgraph in which each vertex has at least degree *k*. The coreness of a vertex is *k* if it belongs to the k-core but not to the ($k+1$)-core" (Csardi and Nepusz, 2006). It is important to underscore that node coreness is derived from but is distinct from graph coreness. Whereas a k-core decomposition identifies nested groups of nodes, the node-level version of this property measures the maximum k-core that a node belongs to in the graph. This latter component of coreness is the measure we used for structural embeddedness. The advantage of using k-core level is that it is a continuous measure of embeddedness, as opposed to a categorical measure (Borgatti and Everett, 2000); this allows us to determine how smaller changes in coreness affect outcomes.

An association between embeddedness and homicide rate may be a function of a neighborhood's underlying propensity for producing co-offenders, rather than the ties these co-offenders create with other neighborhoods. In order to control for this potential bias, we included the following four variables. First, we controlled for the ratio of *inter-to-intra-neighborhood co-offending ties*. We measured intra-neighborhood ties as the number of times two residents of the same neighborhood are arrested together. Inter-neighborhood ties were measured as the sum of weights of adjacent edges of a node. Second, we controlled for the 2001 *neighborhood arrest rate*, which is measured as the number of arrests per neighborhood divided by the population. Third, we included *log population size* in 2001 to control for baseline opportunities for co-offending and violence. Fourth, we included a term for lagged homicide rate to control for a neighborhood's propensity toward crime that is not captured by the other control variables. In this case, we control for the possibility that crime itself increases the propensity for co-offending, or that co-offending partners will likely come from similarly criminogenic neighborhoods. We also ran models that regress k-core on homicide rates to test for this reverse association.

We also controlled for a measure of *degree centrality* (Kadushin, 2011:31), where node degree is defined as the number of adjacent edges (Csardi and Nepusz, 2006). In the 2001 neighborhood co-offending network, degree is highly correlated with our measure of k-core embeddedness ($\rho = 0.84$). The correlation reflects the overlap in how the two measures are constructed: degree captures node-level direct connectivity, while k-core embeddedness reflects both the degree connectivity of the node itself and other nodes in its k-core. The overlap is not complete, however. A neighborhood with a high degree and low embeddedness reflects ties that are potentially more vulnerable to disruption; whereas a neighborhood with a low degree and high embeddedness reflects a small cluster of highly inter-connected neighborhoods. In order to control for the independent effect of degree, we used its residualized version, which is constructed as follows: (1) because initial analyses revealed a strongly positive linear relationship between degree and k-core less than 40, we regressed degree on a linear spline of k-core with a knot at 40; (2) from this model, we calculated predicted values of degree; (3) we subtracted the predicted values from the observed values to obtain residuals. The final values were included in the main analytic models to control for the portion of degree that cannot be explained by embeddedness.

Drawing from 2000 U.S. Census data, we constructed three main neighborhood structure measures that are well established in studies of crime in Chicago (Papachristos et al., 2011). The components of each measure are highly correlated, necessitating a composite measure for each of the three. These measures include: (1) *concentrated disadvantage*, composed of the household poverty rate, percent of families on government assistance, percent of civilians over age 16 who are unemployed, percent of families with children headed by women, and percent of residents who are black; (2) *immigrant concentration*, composed of the percent of residents who are Hispanic and the percent who are foreign born; and (3) *residential stability*, composed of the percent of residents who lived in the same house in 1995 and 2000, and the percent of owner-occupied housing. Following the methods used in Morenoff et al.'s paper (2001:527), we standardized each of the indicators, summed the resulting z-scores, and then divided by the number of indicators in order to construct each scale. This produced a composite measure that evenly weighted each of the original variables.

Additionally, we used measures of *collective efficacy* from the PHDCN. These measures were derived from questions on the PHDCN Community Survey, conducted in 1994–1995. For *collective efficacy*, we replicated the measure used by Sampson et al. (1997). Thus, we combined measures of residents' perceptions of social control, social cohesion and trust. Collective efficacy measures a community's capacity to informally control deviant behavior and take action around shared interests and values (Sampson et al., 1997). Respondents were asked if they would be willing to intervene in the following problems: (1) youth skipping school and hanging out on a street corner, (2) youth spray painting graffiti, (3) youth showing disrespect to an adult, (4) a fight breaking out, and (5) if the local fire station was being closed due to budget cuts. Perceived social cohesion and trust were derived from questions where the respondent was asked to name the extent to which they agreed that (1) people around here are willing to help their neighbors, (2) people in this neighborhood can be trusted, (3) people in this neighborhood generally get along with each other, (4) this is a close-knit neighborhood, and (5) people in this neighborhood share the same values.

4.4. Analytic plan

The main objective of the analysis is to test whether embeddedness influences homicide rates after controlling for inter-neighborhood direct connectivity (degree), the underlying propensity for producing offenders and co-offenders, and neighborhood structural characteristics.[11] We examined the relationship between embeddedness in 2001 and log neighborhood homicide rates in 2002 using a bivariate plot and locally weighted curve fitted to the data. The plot and loess line revealed a slightly positive or no relationship for lower values of embeddedness, and a strongly positive relationship after an embeddedness threshold of approximately 35–40 is reached. Thus, the functional form suggests a tipping point, such that neighborhoods reaching a certain embeddedness level experienced rapid increases in homicide rates.

Given the non-linear discontinuity we observed, we modeled the relationship between embeddedness K in 2001 and the neighborhood homicide rate *Hom* in 2002, controlling for neighborhood variables X using a linear spline with a single knot k. Specifically, we estimated the following model using ordinary least squares (OLS) regression:

$$Log\,(Hom) = \beta_0 + \beta_1 K + \beta_2\,(K-k) + \delta Deg + \gamma X + \varepsilon \tag{1}$$

for $K_{min} \leq k \leq K_{max}$, where K_{min} and K_{max} are the minimum (7) and maximum (50) values of embeddedness observed in our sample and k represents the threshold or tipping point. The effect on the homicide rate changes before and after embeddedness k where the regression function is continuous, but the first derivative is discontinuous. The parameter β_1 is the slope of the segment to the left of k, $\beta_1 + \beta_2$ is the slope of the segment to the right of k, and β_2 is the difference in slopes. If a tipping point at k exists, then $\beta_2 \geq 0$.

We used two methods to obtain a candidate value of k. First, we selected the value k that maximized the R^2 of (1). Hansen (2000) showed that if (1) is correctly specified, this grid-search algorithm yields a consistent estimate of the true change point k. Second, we used segmented regression models (Muggeo, 2003), which estimate breakpoints using an iterative maximum likelihood approach. From a user-defined starting point, the procedure iteratively fits (1) until β_1 and β_2 converges to stable estimates. Note that convergence is not guaranteed, which indicates the potential absence of a true tipping point. Since break points are treated as true model parameters, likelihood-based confidence intervals come as by-products as such models. We used the estimated tipping point from the first procedure as the initial starting point.

For both methods, the estimated tipping point k is 39. Segmented regression models yielded a 95% confidence interval of (36, 42). A drawback of the segmented approach is that threshold estimation can be strongly dependent on the algorithm starting point. However, we found that the estimated tipping point is insensitive to the starting point. Using a random selection of starting points in between 7 and 50, we found that the segmented approach yielded a tipping point of 39 in all cases.

Because homicide rates in a focal neighborhood may be influenced by the homicide rates in its socially proximate neighbors, standard OLS will produce biased results. To address this issue, we estimated a network lag model of the following form (Anselin, 2002; Getis and Aldstadt, 2010; Leenders, 2002):

$$Log\,(Hom) = \beta_0 + \beta_1 K + \beta_2\,(K-k) + \delta Deg + \gamma X + \rho\, WLog\,(Hom) + \varepsilon \tag{2}$$

where ρ is the network lag coefficient, and W is an row-standardized n x n matrix of co-offending network weights. These weights were defined by the number of network ties between neighborhoods whereby network neighbors received a value according to the number of co-offending ties that exist between them, and neighborhood pairs that do not share any co-offending ties received a value of 0. We ran models based on a network where inter-neighborhood ties were defined as present given one or more occurrences of co-offending pairs (we refer to this as a '1-pair' network). We also ran models defining inter-neighborhood ties as five or more co-offending pairs (a '5-pair' network). In the latter case, we test the sensitivity of the results to a stricter criterion for a neighborhood co-offending link. Embeddedness for the 5-pair network ranges from 0 to 13, with a tipping point at 11.

We ran a set of additional models to test the robustness of our main results. First, we ran models with network lags on the error term to control for unobserved network dependencies (e.g. network associations in omitted variables or errors in measurement). Second, we controlled for spatial dependencies in the homicide rate and the error term by running separate spatial lag and error models (Anselin, 2001). Here, W represents a measure of spatial connection between each neighborhood i and j, which in this case is based on first-order queen contiguity. Third, we tested the generalizability of our results across different years of data. Specifically, we examined the effects of embeddedness in 2000 and 2002 on homicide rates one year later (i.e. 2001 and 2003, respectively). For each model, neighborhood structural characteristics remain measured at 2000 whereas degree, the inter-to-intra-neighborhood ties ratio, arrest rates, and log population size were measured during the same year as embeddedness, and lag homicide rates were measured the year prior. Using the same methods from the main analysis, we identified tipping points of 47 and 58 for the 1-pair network and 10 and 12 for the 5-pair network in 2000 and 2002, respectively. Fourth, because we would expect that the current co-offending network has no influence on prior neighborhood homicide rates, we ran a model using the prior year's log homi-

[11] Note that the clustering of nodes along values of 40 and 50 is a reflection of both how the k-core algorithm works and the structure of the network. Specifically, this is due to the fact that degree is updated dynamically in the algorithm we used: "If from a given graph G = (V,L) we recursively delete all vertices of degree less than **k**, and lines incident with them, the remaining graph is the **k**-core of G. Note that when deleting a vertex the degrees of its neighbors decrease" (Batagelj and Zaversnik, 2011: 131). We observed similar patterns, i.e. multiple clusters near the higher end of the distribution, in co-offending networks that we constructed for 2000 and 2002 as well.

cide rate as the dependent variable – in other words measuring the effect of 2001 embeddedness on 2000 log homicide rates. Fifth, we tested the directionality of the association between embeddedness and homicide rates. We tested whether homicide rates affected future embeddedness by regressing the k-core in 2002 on homicide rates in 2001. We also expect that future homicide should have no influence on past embeddedness. Therefore, our final sensitivity test regressed embeddedness in 2001 on log homicide rates in 2002. For both of these tests, the outcome is a binary variable indicating whether embeddedness is equal or above the identified tipping point. Full results of these sensitivity tests are provided in the Appendix.

5. Results

5.1. Descriptive results

The 2001 neighborhood co-offending network is comprised of a single component – i.e., all 342 neighborhoods in this network are directly or indirectly connected to one another, and there are no isolated nodes in this network. The density of this network, at 0.21, is quite high, and indicates that 21 percent of all possible ties are present. Additionally, average degree is 70.98, indicating that the level of direct ties between neighborhoods is quite high as well.[12] Fig. 1 depicts this highly connected network, highlighting the k-core structure.[13] Here, nodes are arranged and colored according to coreness, with nodes that make up the highest possible k-core located at the center of the graph, and more peripheral nodes located at the outer rings of the graph. Recall that k-core decomposition yields nested groups of nodes: all 342 nodes are part of the minimum k-core, the 7-core, but weakly connected nodes are 'pruned' as we move from the 7-core to the more densely connected inner cores. The maximum k-core appears at the center of the image, and consists of 123 neighborhood-nodes (approximately 36 percent of all nodes) that each have a degree of 50 or higher within this highly connected sub-community of nodes.[14] Recall that our main independent variable, structural embeddedness, is related to but also distinct from the overlapping graph-level core structure: structural embeddedness captures a node's maximum k-core level, i.e. the highest k-core community to which a node belongs.

In Fig. 2, selected k-cores are displayed using a spatial layout. This figure illustrates a key descriptive finding: though many co-offending ties are spatially concentrated among neighborhoods in the West Side and South Side of Chicago, we also see that many ties reach between neighborhoods that are not spatial neighborhoods, and in some cases, between neighborhoods that are separated by substantial geographic distances. This is true at lower and higher k-core levels, though the geographic reach of co-offending ties does shrink as we move from the 24-core to the 50-core. This suggests that embeddedness is not a completely geographically dependent process—low-embedded neighborhoods can coexist with nearby highly-embedded communities.

The 24-core consists of 309 neighborhoods; neighborhoods are shaded by degree centrality within this 24-core. Neighborhoods located in Chicago's high crime areas–the West and South Sides–appear to have the most direct ties within this sub-community. The 41-core and 50-core consist of 205 nodes and 123 nodes, respectively. Here, weakly connected nodes have been pruned away, and we are left with a sub-community of nodes that are highly connected and which are above the embeddedness threshold of 39. Importantly, the 50-core sub-community of nodes is clearly not vulnerable to the removal of one or even a few inter-neighborhood ties: each neighborhood is connected to at least 50 other neighborhoods, which are all also connected to at least 50 other neighborhoods. This suggests that modeling the diffusion of violence by using information about direct connections alone is a limited approach, as it masks the extent of variation in the strength of interdependence between neighborhoods.

These descriptive results indicate that inter-neighborhood co-offending ties are not explained by geographic proximity alone. Moreover, they suggest that direct connectivity between pairs of neighborhoods is limited, as it does not account for other dimensions of connectivity that are captured by k-core embeddedness, including indirect ties and the extent of redundant ties among a node's network neighbors. We examine the relationship between k-core embeddedness and local rates of violence further in the following section.

5.2. Analytic results

Table 2 presents results for our main multivariate models, which examine whether neighborhood homicide rates are explained by a neighborhood's structural embeddedness within the larger neighborhood co-offending network. The coefficients for the k-core spline test whether embeddedness within a larger cohesive neighborhood structure affect homicide rates before and after a certain threshold. Results for both the 1-pair and 5-pair network models show threshold effects at k whereby embeddedness before k is not significant, but embededdness after k exhibits a statistically significant positive association with the homicide rate.

The OLS results displayed in the first and second columns of Table 2 are likely problematic because they do not account for the presence of spatial and network dependencies. We used Moran's I (Bailey and Gattrell, 1995) to measure global spatial autocorrelation in the residuals; it is positive and statistically significant for both the 1-pair and 5-pair OLS models. The third and fourth columns show results from network lag models using 1-pair and 5-pair networks, respectively. In contrast to the OLS models, the Moran's I results for both network lag models indicate no presence of spatial autocorrelation in the residuals. Here, the 1-pair model exhibits a lower AIC and thus a better fit than the 5-pair network lag model. Moreover, the 1-pair model captures the citywide network whereas the 5-pair model captures a narrower network, reflecting a stricter definition for inter-neighborhood co-offending ties. Results from the 1-pair network lag model indicate that a one-unit increase in residential stability is associated with a 15.0% ($e^{0.14}$) increase in the subsequent homicide rate within the same neighborhood, on average. Concentrated disadvantage, concentrated immigration and collective efficacy do not have statistically significant relationships with the homicide rate. We find that a 10% increase in population size is associated with a 2.9% decrease in homicide rates. Node degree is positively associated with homicide rates, indicating that an additional neighborhood-level link increases the neighborhood homicide rate by 1.0% ($e^{0.01}$). Additionally, a 10% increase in the 2001 homicide rate is associated with a 2.8% increase in the 2002 homicide rate. These results corroborate previous findings that establish the importance of neighborhood structural disadvantage and direct neighborhood connectivity in explaining local homicide rates.

For neighborhoods with a k-core less than 39, a one-unit increase in k-core is associated with a 1.0% ($e^{0.01}$) increase in homicide rates. However, this association is not statistically significant at

[12] Again, we note that the structure of Chicago co-offending networks for 1999–2004 have been examined elsewhere, and are very stable during that six-year time period (Charette and Papachristos, 2017).

[13] We drew heavily from Alvarez-Hamelin et al.'s (2006) k-core decomposition algorithm in designing this layout.

[14] Note that degree here is distinct from node degree in the original graph, as node degree is dynamically updated as weakly connected nodes are pruned to obtain k-cores.

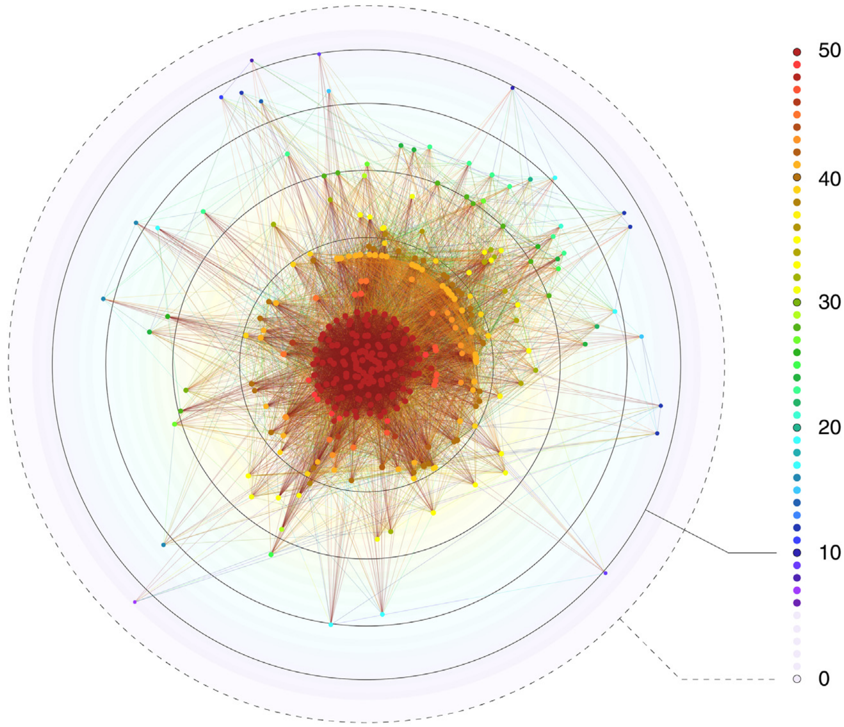

Fig. 1. Network k-core structure. The maximum k-core appears at the center, and consists of 123 neighborhood-nodes (approximately 36 percent of all nodes) that each have a degree of 50 or higher within this highly connected sub-community of nodes.

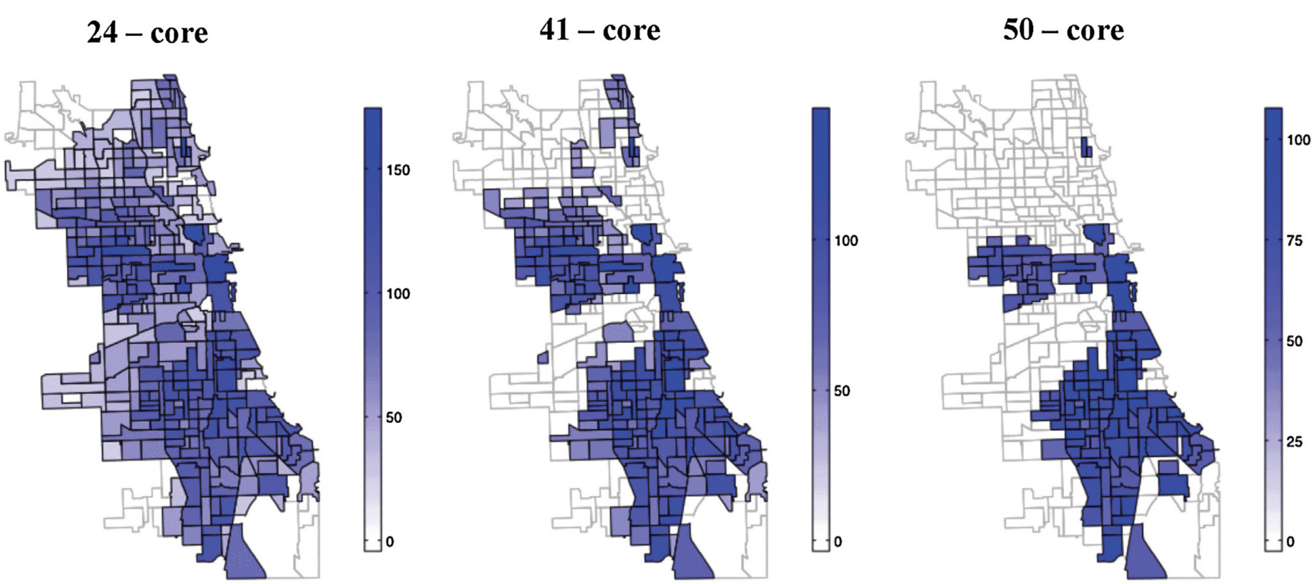

Fig. 2. Maps of selected k-cores. Network ties connect spatially proximate *and* spatially distant neighborhoods.
Note: Neighborhood-nodes are shaded by degree centrality within the selected k-core community.

conventional levels. In contrast, the positive relationship between k-core and homicide rates for k-core values equal to or greater than 39 is statistically significant and considerably larger – a one-unit increase is associated with a 5.1% ($e^{0.05}$) increase in homicide rates. Moreover, the difference in slopes between k-core $\geq$ 39 and k-core <39 (0.05–0.01 = 0.04) is statistically significant (standard error of 0.01; *p*-value of 0.002). These results indicate an embeddedness threshold or tipping point in neighborhood-level crime. In this case, increasing embeddedness for neighborhoods with a k-core less than 39 does not change their homicide rates. However, after embeddedness reaches and "tips" over 39, homicide rates increase by 5.1% for every one-unit increase in k-core.

The last column in Table 2 shows results for models using a 5-pair co-offending network. The results for the control variables do not differ substantially from those produced by the 1-pair model. More importantly, coreness also exhibits a threshold effect in the 5-pair network – the slope for embeddedness is positive and significant only after a value of 11 is reached. The threshold effect here is much larger than in the 1-pair model – homicide rates increase by 24.6% ($e^{0.22}$) for every one-unit increase in embeddedness after a k-core of 11. This is not unexpected, as it reflects the

Table 2
Coefficients and Standard Errors from OLS and Network Lag Regression Models Predicting Log Empirical Bayes Homicide Rates in 2002.

	OLS		Network lag	
Variable	1-pair	5-pair	1-pair	5-pair
Intercept	−2.88**	−3.92***	−1.70	−3.65***
	(0.95)	(0.91)	(1.55)	(0.94)
Embeddedness, 2001[a]				
K-core < k	0.01	0.02	0.01	0.02
	(0.01)	(0.01)	(0.17)	(0.16)
K-core ≥ k	0.05***	0.21**	0.05**	0.22**
	(0.02)	(0.07)	(0.17)	(0.15)
Control Variables				
Log Homicide Rate, 2001	0.29***	0.31***	0.29***	0.31***
	(0.05)	(0.05)	(0.05)	(0.05)
Concentrated Disadvantage, 2000	0.15	0.20**	0.14	0.19**
	(0.08)	(0.07)	(0.08)	(0.07)
Concentrated Immigration, 2000	0.01	0.02	0.01	0.02
	(0.05)	(0.04)	(0.05)	(0.04)
Residential Stability, 2000	0.15***	0.14***	0.14***	0.13***
	(0.04)	(0.04)	(0.04)	(0.04)
Collective Efficacy, 1994–95	−0.18	−0.19	−0.17	−0.18
	(0.13)	(0.13)	(0.13)	(0.13)
Log Population Size, 2001	−0.32***	−0.17*	−0.31***	−0.17*
	(0.09)	(0.08)	(0.08)	(0.08)
Inter-to-Intra Neighborhood Ties Ratio, 2001	−0.02	−0.08*	−0.02	−0.08*
	(0.03)	(0.04)	(0.03)	(0.04)
Arrest Rate, 2001	−0.27	0.12	−0.25	0.12
	(0.44)	(0.42)	(0.43)	(0.41)
Degree, 2001	0.01***	0.01	0.01***	0.01*
	(0.002)	(0.004)	(0.002)	(0.004)
ρ[b]			0.16	0.03
			(0.16)	(0.03)
LM test, residual autocorrelation[c]			Not sig.	Not sig.
Moran's *I*, residuals	***	***	Not sig.	Not sig.
AIC	478.50	487.18	479.53	488.20

***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05.
[a]The threshold *k* is 39 and 11 in the 1-pair and 5-pair models, respectively. Differences in slopes before and after *k* are statistically significant.
[b]Network lag parameter.
[c]Test against a null of spatial independence in the residuals
Standard errors are in parentheses.

pared-down network in which the criterion for defining an inter-neighborhood tie is stricter. Overall, the results for the 1- and 5-pair network lag models suggest that the further entrenching of a neighborhood in a broader criminal network of neighborhoods through the creation of co-offending ties increases homicide rates in that neighborhood even after controlling for the effects of its direct connectivity to other nodes, prior homicide rates, latent production of co-offenders, the ratio of inter-to-intra neighborhood co-offending ties, and structural disadvantage.

The results of the sensitivity tests presented in the Appendix were largely consistent with the main results. In particular, embeddedness exhibited a threshold effect in both 1-pair and 5-pair network error models, which accounts for unobserved network interdependencies, and in separate spatial lag and error models, which account for spatial interdependencies in the dependent variable and error term, respectively. Moreover, the 1-pair and 5-pair network lag models exhibited better fit compared to their spatial lag counterparts with respect to the AIC and Lagrange multiplier tests of spatial dependence, which indicates that violent crime diffuses through co-offending neighborhood ties independent of any diffusion via unobserved network interdependencies and spatial adjacency.

6. Discussion and conclusion

This study proposes a new, multidimensional approach for classifying urban neighborhoods, one we hypothesized would shed light on the unequal distribution of crime and violence in cities. As anticipated, our findings indicate that a neighborhood's structural embeddedness within Chicago's neighborhood co-offending network influences its subsequent homicide rate. This relationship holds even after accounting for neighborhoods' internal propensity toward violent crime, and network interdependence between pairs of neighborhoods. However, the strong positive relationship is observed only after a threshold is breached: in other words, structural embeddedness must reach a certain level before it begins to have an impact on neighborhood violent crime. These results are robust across a number of different model specifications.

This study is not without limitations, several of which we address here. First, our main network lag models are cross-sectional in nature. As with other work that employs cross-sectional spatial or network lag models to examine the diffusion of violence (which we provide many citations to in the introduction), we are not directly measuring changes in rates of violence over time and across space. Instead, we rely on a standard interpretation of our models to infer that neighborhoods connected via a co-offending network mutually and collectively influence each other's crime rates. Second, we acknowledge that our analytic approach, i.e. using a network lag model, is one of many methods that could be applied here. Future work ought to examine the properties of inter-neighborhood co-offending networks, and what contributes to tie formation between neighborhoods.

Our findings have important implications for future research and policy. First, our results provide a new descriptive approach to categorizing urban neighborhoods. Specifically, we identified supra-neighborhood groups that are consequential for social life at the neighborhood level. This method does not need to be limited to studies of crime–it could potentially be applied to any outcome for which relevant social network data are available. Second, our explanatory results suggest that future work on the diffusion of violent crime ought to pay more attention to the broader social organization of cities, in addition to ego- or dyad-centric approaches that are common to standard spatial and network lag models.

Notably, our results suggest that network relationships may help explain persistent inequalities in neighborhood crime, as neighborhoods with the worst crime rates may 'lock' each other in place such that a given neighborhood's relative crime rate over the long-term is determined by the characteristics of a larger, socially cohesive sub-group of high crime neighborhoods. This last point is further exemplified by the finding that embeddedness matters after a threshold is breached, suggesting that the diffusion of violence from one neighborhood to the next may only have a notable impact within neighborhoods that are deeply entrenched in the city-wide co-offending network. The substantively meaningful finding here is not about the absolute threshold value of 39, but rather the presence of a tipping point that, relative to the distribution, falls at the higher end of network embeddedness: threshold values near the top of the distribution were found in the 1-pair and 5-pair networks for 2001, as well as for other years of data. These results align with a mechanism that we proposed earlier, i.e., that these highly embedded neighborhoods are repeatedly exposed to criminogenic influences from multiple sources. Moreover, those sources are also highly connected within the network, such that deviant social norms or other resources supporting criminal activity may be circulating intensely within subgroups of highly embedded neighborhoods, but weakly in less embedded neighborhoods. Others have noted that autocorrelation models[15] are constrained because the autocorrelation term, ρ, is an average measure of influence, and is "insensitive to variation in degree. . .across nodes in the network" (Gould, 1991: 723). In this vein, our results suggest that previous work documenting an average spillover effect between all pairs of connected neighborhoods may *actually* be capturing intense diffusion within a smaller subset of densely connected neighborhoods. The implications of this are significant, as, if this is the case, previous work has both *underestimated* the true interdependence of violence within the most embedded neighborhoods, while *overestimating* this problem within the least embedded neighborhoods. Future work ought to examine heterogeneity in diffusion effects in other settings.

From a policy perspective, a neighborhood-level intervention that incorporates our findings will adopt different strategies depending on a neighborhood's location along the k-core distribution. A targeted approach to preventing crime in the city could develop different strategies for high versus low-embedded communities throughout the city. Our results suggest that in neighborhoods at the low end of the distribution, below the k-core threshold level, crime can be targeted one neighborhood at a time. Disentangling highly embedded neighborhoods from the broader criminal network, however, is likely to require targeting groups of highly connected neighborhoods, rather than focusing on particular hot spots in isolation. It may be more effective to target anti-violence prevention efforts to neighborhoods that are within the same socially cohesive sub-group. Importantly, these implications align well with urban policy recommendations recently proposed by Sampson (2012) and Sharkey (2013); namely, that in order to be effective, urban policy needs to account for how cities function as interconnected wholes, but also provide tailored support to neighborhoods that are disadvantaged and historically underserved. We suggest that the present study provides both a new conceptual frame and an empirical approach for identifying neighborhoods that require the most assistance and intervention, and also for understanding the deeply rooted nature of inequality. Future studies ought to pursue this line of thinking, as it may prove fruitful for developing innovative and effective anti-violence interventions in American cities.

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Appendix.

In the main analyses, we examined the association between embeddedness in 2001 and neighborhood homicide rates in 2002 using ordinary least squares (OLS) and network lag regression models using 1-pair and 5-pair co-offending networks. In each model, we controlled for neighborhood structural characteristics, log population size, neighborhood arrest rates, degree centrality, and the ratio of inter-to-intra neighborhood co-offending ties.

We ran a set of additional models to test the robustness of our main results. First, we ran models with network lags on the error term to control for unobserved network dependencies (e.g. network associations in omitted variables or errors in measurement). Second, we controlled for spatial dependencies in the homicide rate and the error term by running spatial lag and error models (Anselin, 2001). Here, *W* represents a measure of spatial connection between each neighborhood *i* and *j*, which in this case is based on first-order queen contiguity. We found that the results from these models do not diverge from the findings in the main analyses (Table A1).

Third, we tested the generalizability of our results across different years of data. Specifically, we examined the effects of embeddedness in 2000 and 2002 on homicide rates one year later (i.e. 2001 and 2003). For each model, neighborhood structural characteristics remain measured at 2000 whereas degree, the inter-to-intra-neighborhood ties ratio, arrest rates, and log population size were measured during the same year as embeddedness, and lag homicide rates were measured the year prior. Using the same methods from the main analysis, we identified tipping points of 47 and 58 for the 1-pair network and 10 and 12 for the 5-pair network in 2000 and 2002, respectively. We found similar results to the main findings for the 2000–01 1-pair network and 5-pair spatial lag models (Table A2), as well as the 2002–03 1-pair network and spatial error models (Table A3). We found in the 2000–01 5-pair network and spatial error models that the slopes before and after the threshold were significant from 0 and one another, with the

[15] In cases where the weights matrix is row-standardized, which is the typical approach.

Table A1
Coefficients and Standard Errors from Network Error and Spatial Lag and Error Models Predicting Log Empirical Bayes Homicide Rates in 2002.

	1 Pair			5 Pair		
Variable	Spatial Error	Spatial Lag	Network Error	Spatial Error	Spatial Lag	Network Error
Intercept	−2.99**	−1.84	−2.88**	−4.06***	−2.80**	−3.97***
	(0.94)	(1.01)	(0.94)	(0.91)	(0.98)	(0.90)
Embeddedness, 2001[a]						
K-core < k	0.01	0.01	0.01	0.02	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
K-core ≥ k	0.05***	0.04**	0.05***	0.20**	0.17*	0.21**
	(0.02)	(0.02)	(0.01)	(0.07)	(0.07)	(0.07)
Control Variables						
Log Homicide Rate, 2001	0.28***	0.26***	0.29***	0.29***	0.27***	0.30***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Concentrated Disadvantage, 2000	0.15	0.11	0.14	0.20**	0.14	0.19**
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
Concentrated Immigration, 2000	0.01	0.00	0.00	0.02	0.03	0.03
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Residential Stability, 2000	0.15***	0.13***	0.15***	0.14***	0.12**	0.14***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Collective Efficacy, 1994-95	−0.17	−0.16	−0.18	−0.18	−0.17	−0.21
	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)
Log Population Size, 2001	−0.32***	−0.29***	−0.32***	−0.17*	−0.14	−0.16*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Inter-to-Intra Neighborhood Ties Ratio, 2001	−0.03	−0.02	−0.02	−0.08*	−0.07	−0.07
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Arrest Rate, 2001	−0.27	−0.10	−0.27	0.13	0.34	0.22
	(0.43)	(0.43)	(0.43)	(0.42)	(0.41)	(0.41)
Degree, 2001	0.01***	0.01***	0.01***	0.01	0.01	0.01
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
ρ[b]		0.18**			0.20**	
		(0.06)			(0.06)	
λ[c]	0.08		0.03	0.09		0.16
	(0.09)		(0.28)	(0.09)		(0.11)
LM test, residual autocorrelation[d]	*	*	Not sig.	*	*	Not sig.
Moran's *I*, residuals	Not sig.	*	Not sig.	Not sig.	*	Not sig.
AIC	479.66	472.76	480.50	488.30	479.88	487.68

***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05.
[a]The threshold *k* is 39 and 11 in the 1-pair and 5-pair models, respectively. Differences in slopes before and after *k* are statistically significant.
[b]Lag parameter.
[c]Error parameter
[d]Test against a null of spatial independence in the residuals
Standard errors are in parentheses.

slope after the threshold significantly larger, indicating a threshold effect whereby neighborhoods reaching a threshold experienced a stronger association between their embeddedness in the citywide co-offending network and local homicide rates. We found in the 2002–03 5-pair models and the 1-pair spatial lag models that the slopes before and after the threshold do not differ. In these cases, we reran the models without the spline, and found a statistically significant linear effect of k-core on homicide rates, which indicates a relationship between embeddedness and homicide with no tipping point. The 2000–01 1-pair spatial models yield no statistically significant associations between embeddedness and homicide rates. We also found that the overall fit is better in the network models relative to the spatial models.

Fourth, because we would expect that the current co-offending network has no influence on prior neighborhood homicide rates, we ran a model using the prior year's log homicide rate as the dependent variable – in other words, measuring the effect of 2001 embeddedness on 2000 log homicide rates. We found that most models yield no statistically significant associations between k-core in 2001 and homicide rates in 2000 (Table A4). The only exceptions are the 1-pair spatial and network error models, which yielded statistically significant threshold effects.

Fifth, we tested the directionality of the association between embeddedness and homicide rates. We tested whether homicide rates affected future embeddedness by regressing the k-core in 2002 on homicide rates in 2001. We also expect that homicide should have no influence on past embeddedness. Therefore, our final sensitivity test regressed embeddedness in 2001 on log homicide rates in 2002. For both of these tests, the outcome is a binary variable indicating whether embeddedness is equal to or above the identified tipping point. We found no statistically significant association between homicide rates in 2001 and embeddedness in 2002, indicating that the causal direction runs from embeddedness to homicides and not vice versa (Table A5). We also found no significant relationship between homicide rates in 2002 and embeddedness in 2001 in the 5-pair models (Table A6); however, we found a statistically significant negative association between these two variables in the 1-pair models.

In summary, the results of the sensitivity tests were largely consistent with the main results. Most models using different years of data exhibited threshold effects, with the network lag and error models exhibiting better fit than their spatial counterparts. We largely found no effects of embeddedness on prior homicide rates. We also found little evidence that homicide rates impact embeddedness, whether measured in the past or the future.

Table A2
Coefficients and Standard Errors from Spatial and Network Lag and Error Models Predicting Log Empirical Bayes Homicide Rates in 2001.

	1-pair				5-pair			
Variable	Spatial Error	Spatial Lag	Network Error	Network Lag	Spatial Error	Spatial Lag	Network Error	Network Lag
Intercept	−6.36***	−4.65***	−6.09***	−4.80***	−6.35***	−4.87***	−6.00***	−6.06***
	(1.07)	(1.14)	(1.06)	(1.42)	(1.06)	(1.16)	(1.05)	(1.08)
Embeddedness, 2000[a]								
K-core < k	0.002	0.002	0.004	0.004	0.03*	0.02	0.03*	0.03*
	(0.01)	(0.004)	(0.004)	(0.004)	(0.02)	(0.01)	(0.01)	(0.01)
K-core ≥ k	0.07	0.05	0.07*	0.07*	0.10**	0.08*	0.10***	0.10***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Control Variables								
Log Homicide Rate, 2000	0.17**	0.17**	0.21***	0.19***	0.16**	0.16**	0.19***	0.19***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Concentrated Disadvantage, 2000	0.24**	0.20*	0.25**	0.23**	0.22**	0.19*	0.21**	0.22**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Concentrated Immigration, 2000	0.08	0.07	0.07	0.07	0.07	0.06	0.07	0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Residential Stability, 2000	0.06	0.06	0.08	0.07	0.05	0.05	0.06	0.06
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Collective Efficacy, 1994-95	−0.15	−0.16	−0.19	−0.19	−0.11	−0.14	−0.16	−0.15
	(0.15)	(0.14)	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)
Log Population Size, 2000	−0.06	−0.04	−0.05	−0.06	−0.09	−0.07	−0.08	−0.08
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)
Inter-to-Intra Neighborhood Ties Ratio, 2000	0.05	0.05	0.07	0.06	0.02	0.02	0.03	0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Arrest Rate, 2000	0.79*	0.74*	0.71*	0.68*	0.67*	0.62*	0.59	0.57
	(0.34)	(0.33)	(0.34)	(0.33)	(0.32)	(0.31)	(0.31)	(0.32)
Degree, 2000	0.001	0.001	0.001	0.001	−0.0001	0.00002	−0.004	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.01)	(0.01)	(0.01)	(0.01)
ρ[b]		0.22**		0.15		0.18*		0.002
		(0.07)		(0.11)		(0.07)		(0.02)
λ[c]	0.24**		0.02		0.21*		−0.06	
	(0.08)		(0.20)		(0.08)		(0.10)	
LM test, residual autocorrelation[d]	*	*	Not sig.	Not sig.	*	*	Not sig.	Not sig.
Moran's *I*, residuals	Not sig.	*	Not sig.	Not sig.	Not sig.	*	Not sig.	Not sig.
AIC	572.69	569.59	579.85	577.95	568.09	566.90	572.91	573.18

***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$.
[a]The threshold *k* is 50 and 10 in the 1-pair and 5-pair models, respectively. Differences in slopes before and after *k* are statistically significant.
[b]Lag parameter.
[c]Error parameter.
[d]Test against a null of spatial independence in the residuals.
Standard errors are in parentheses.

Table A3
Coefficients and Standard Errors from Spatial and Network Lag and Error Models Predicting Log Empirical Bayes Homicide Rates in 2003.

	1-pair				5-pair			
Variable	Spatial Error	Spatial Lag	Network Error	Network Lag	Spatial Error	Spatial Lag	Network Error	Network Lag
Intercept	−3.66***	−2.21*	−3.61***	−1.40	−3.71***	−2.46*	−3.52***	−3.47**
	(1.07)	(1.12)	(1.05)	(1.72)	(1.07)	(1.13)	(1.06)	(1.06)
Embeddedness, 2002[a]								
K-core < k	0.01	0.004	0.01	0.004	0.03*	0.02	0.03*	0.03*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
K-core ≥ k	0.06*	0.05	0.05*	0.05	0.04**	0.03*	0.04**	0.04**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Control Variables								
Log Homicide Rate, 2002	0.26***	0.25***	0.28***	0.29***	0.27***	0.26***	0.30***	0.30***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Concentrated Disadvantage, 2000	0.22***	0.16*	0.23**	0.21**	0.19*	0.14	0.19*	0.19*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Concentrated Immigration, 2000	−0.05	−0.04	−0.04	−0.05	−0.08	−0.06	−0.08	−0.08
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Residential Stability, 2000	0.12*	0.10*	0.13**	0.12**	0.10*	0.09*	0.11*	0.11*
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Collective Efficacy, 1994–95	−0.40**	−0.39**	−0.40**	−0.44**	−0.40**	−0.39**	−0.41**	−0.43**
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Log Population Size, 2002	−0.18	−0.14	−0.17	−0.16	−0.15	−0.12	−0.14	−0.14
	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Inter-to-Intra Neighborhood Ties Ratio, 2002	0.01	0.01	0.03	0.02	0.004	0.003	0.005	0.003
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Arrest Rate, 2002	−0.94	−0.16	−0.24	−0.56	−0.43	−0.19	−0.22	−0.31
	(1.30)	(1.26)	(1.25)	(1.27)	(1.27)	(1.24)	(1.24)	(1.25)
Degree, 2002	0.004*	0.003*	0.003*	0.003*	0.001	0.001	0.001	0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
ρ[b]		0.21**		0.21		0.19**		0.001
		(0.07)		(0.15)		(0.07)		(0.02)
λ[c]	0.14		0.45*		0.11		0.06	
	(0.08)		(0.18)		(0.09)		(0.10)	
LM test, residual autocorrelation[d]	*	*	Not sig.	*	*	*	Not sig.	Not sig.
Moran's I, residuals	Not sig.	Not sig.	Not sig.	*	Not sig.	Not sig.	Not sig.	Not sig.
AIC	607.35	600.26	605.36	607.98	605.99	599.70	606.98	607.22

***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05.
[a]The threshold *k* is 58 and 12 in the 1-pair and 5-pair models, respectively. Differences in slopes before and after *k* are statistically significant.
[b]Lag parameter.
[c]Error parameter.
[d]Test against a null of spatial independence in the residuals.
Standard errors are in parentheses.

Table A4
Coefficients and Standard Errors from Spatial and Network Lag and Error Models Predicting Log Empirical Bayes Homicide Rates in 2000.

	1-pair				5-pair			
Variable	Spatial Error	Spatial Lag	Network Error	Network Lag	Spatial Error	Spatial Lag	Network Error	Network Lag
Intercept	−3.64***	−2.33*	−3.67***	−0.84	−4.67***	−3.36**	−4.68***	−4.52***
	(1.01)	(1.07)	(1.01)	(1.57)	(0.97)	(1.04)	(0.96)	(1.01)
Embeddedness, 2001[a]								
K-core < k	0.01	0.004	0.01	0.01	0.02	0.01	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
K-core ≥ k	0.04*	0.03	0.04*	0.03	0.12	0.08	0.11	0.12
	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)	(0.08)	(0.08)	(0.08)
Control Variables								
Log Homicide Rate, 2001	0.18***	0.16***	0.19***	0.18***	0.20***	0.18***	0.22***	0.20***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Concentrated Disadvantage, 2000	0.30***	0.24**	0.31***	0.29***	0.37***	0.29***	0.38***	0.37***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Concentrated Immigration	0.05	0.04	0.04	0.05	0.04	0.04	0.05	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Residential Stability, 2000	0.08	0.06	0.08	0.08	0.07	0.05	0.07	0.07
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Collective Efficacy, 2000	−0.26	−0.25	−0.26	−0.25	−0.27*	−0.26	−0.25	−0.27
	(0.14)	(0.13)	(0.14)	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)
Log Population Size, 2001	−0.31***	−0.27**	−0.31***	−0.27**	−0.16	−0.13	−0.15	−0.16
	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)
Inter-to-Intra Neighborhood Ties Ratio, 2001	0.003	0.01	0.003	0.01	−0.03	−0.02	−0.04	−0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Arrest Rate, 2001	−0.13	0.03	−0.14	−0.09	0.23	0.42	0.20	0.22
	(0.46)	(0.46)	(0.46)	(0.46)	(0.45)	(0.44)	(0.45)	(0.45)
Degree, 2001	0.01***	0.01***	0.01***	0.01***	0.01	0.01	0.01	0.01
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
ρ[b]		0.20**		0.37*		0.20**		0.02
		(0.06)		(0.16)		(0.06)		(0.03)
λ[c]	0.05		0.06		0.02		−0.16	
	(0.09)		(0.28)		(0.09)		(0.11)	
LM test, residual autocorrelation[d]	*	*	Not sig.	Not sig.	**	**	Not sig.	Not sig.
Moran's I, residuals	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.
AIC	529.50	521.87	529.77	524.54	541.79	533.74	540.18	541.60

***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$.
[a]The threshold k is 39 and 11 in the 1-pair and 5-pair models, respectively. Differences in slopes before and after k are statistically significant.
[b]Lag parameter.
[c]Error parameter.
[d]Test against a null of spatial independence in the residuals.
Standard errors are in parentheses.

Table A5
Coefficients and Standard Errors from Spatial and Network Lag and Error Models Predicting Embeddedness in 2002.

	1-pair				5-pair			
Variable	Spatial Error	Spatial Lag	Network Error	Network Lag	Spatial Error	Spatial Lag	Network Error	Network Lag
Intercept	0.01	−0.41	0.32	−0.44	−1.13	−1.67**	−0.95	−1.09
	(0.65)	(0.63)	(0.65)	(0.67)	(0.60)	(0.58)	(0.71)	(0.74)
Log Homicide Rate, 2001[a]	−0.002	−0.002	0.02	0.01	0.003	−0.003	0.06	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Control Variables								
Concentrated Disadvantage, 2000	0.10	0.07	0.08	0.07	0.07	0.04	0.11*	0.10
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Concentrated Immigration, 2000	0.11***	0.09***	0.10**	0.11***	−0.05	−0.01	−0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)
Residential Stability, 2000	0.04	0.03	0.04	0.03	−0.01	0.01	−0.02	−0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)
Collective Efficacy, 1994–95	−0.03	−0.01	−0.04	−0.01	−0.14	−0.09	−0.02	−0.08
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.10)	(0.10)
Log Population Size, 2001	0.03	0.05	0.01	0.03	0.22***	0.22	0.19**	0.20**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)
Inter-to-Intra Neighborhood Ties Ratio, 2001	0.003	0.01	0.004	0.01	−0.07**	−0.05*	−0.10***	−0.07*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Arrest Rate, 2001	−0.43	−0.33	−0.56	−0.44	0.51	0.70**	0.77*	0.86*
	(0.31)	(0.29)	(0.30)	(0.29)	(0.30)	(0.27)	(0.32)	(0.34)
Degree, 2001	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
ρ[a]		0.63***		0.13		0.32***		0.60**
		(0.05)		(0.09)		(0.06)		(0.16)
λ[b]	0.31***		0.69**		0.69***		0.49***	
	(0.08)		(0.16)		(0.05)		(0.10)	
LM test, residual autocorrelation[c]	Not sig.	Not sig.	Not sig.	Not sig.	**	Not sig.	***	***
Moran's *I*, residuals	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.	**
AIC	234.93	226.84	240.75	239.36	220.63	220.14	334.13	349.68

***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$.
[a]Lag parameter.
[b]Error parameter.
[c]Test against a null of spatial independence in the residuals.
Standard errors are in parentheses.

Table A6
Coefficients and Standard Errors from Spatial and Network Lag and Error Models Predicting Embeddedness in 2001.

	1-pair				5-pair			
Variable	Spatial Error	Spatial Lag	Network Error	Network Lag	Spatial Error	Spatial Lag	Network Error	Network Lag
Intercept	0.19	−0.21	0.87	−0.32	0.34	0.10	0.51	−0.11
	(0.54)	(0.52)	(0.54)	(0.54)	(0.63)	(0.62)	(0.62)	(0.62)
Log Homicide Rate, 2002[a]	−0.08*	−0.08**	−0.07*	−0.07*	0.02	0.01	0.03	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Control Variables								
Concentrated Disadvantage, 2000	0.09	0.04	0.03	0.02	0.04	0.02	0.03	0.03
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Concentrated Immigration, 2000	0.07**	0.06**	0.07**	0.08***	−0.06*	−0.05	−0.06*	−0.05
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Residential stability, 2000	−0.002	0.01	0.01	0.01	−0.001	0.01	0.003	0.003
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Collective Efficacy, 1994–95	−0.02	−0.04	−0.08	−0.04	−0.08	−0.08	−0.10	−0.08
	(0.08)	(0.07)	(0.08)	(0.07)	(0.09)	(0.09)	(0.09)	(0.09)
Log Population Size, 2001	−0.06	−0.04	−0.12*	−0.08	0.03	0.04	0.02	0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Inter-to-Intra Neighborhood Ties Ratio, 2001	−0.02	−0.03	−0.04*	−0.03	−0.01	−0.01	−0.02	−0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
Arrest Rate, 2001	−0.58*	−0.41	−0.60*	−0.44	0.01	0.09	0.02	0.06
	(0.26)	(0.24)	(0.25)	(0.24)	(0.30)	(0.29)	(0.29)	(0.28)
Degree, 2001	0.01***	0.01***	0.01***	0.01***	0.03***	0.03***	0.03***	0.03
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
ρ^a		0.33***		0.76***		0.17*		0.33**
		(0.06)		(0.11)		(0.07)		(0.07)
λ^b	0.33***		0.14		0.13		0.06	
	(0.08)		(0.27)		(0.09)		(0.11)	
LM test, residual autocorrelation[c]	Not sig.	Not sig.	***	**	Not sig.	Not sig.	Not sig.	Not sig.
Moran's I, residuals	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.	Not sig.
AIC	124.52	108.56	137.41	115.48	243.67	239.21	245.38	230.70

***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$.
[a]Lag parameter.
[b]Error parameter
[c]Test against a null of spatial independence in the residuals.
Standard errors are in parentheses.

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