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ORIGINAL PAPER

Spatial Networks of Neighborhood Violence

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Abstract

Purpose We propose a network approach to studying neighbourhood violence that shifts the focus away from explaining crime levels of individual neighbourhoods towards models that explain citywide networks of crime correlations. Our conceptualization places the network of inter-neighbourhood crime correlations as the phenomenon to be explained: why some pairs of neighbourhoods have crime rates that are highly correlated, and others do not.

Methods We use Exponential Random Graph Models (ERGMs) to implement this framework empirically. ERGMS are applied to correlated trends in shooting incidents across neighbourhoods in Chicago. Our models attempt to explain inter-neighbourhood crime correlations in terms of three mechanisms: *spatial proximity*, *neighbourhood homophily* (neighbourhoods are more likely to be connected in terms of crime correlations if they share underlying characteristics associated with violence), and *flows of people* across neighbourhoods based on 2019 Safegraph mobile phone GPS daily mobility data.

Results Whilst spatial proximity of neighbourhoods plays a role in explaining correlations in shooting between neighbourhoods, we also find crime correlations between distant neighbourhoods, driven by socioeconomic proximity (similarity of neighbourhoods in terms of their socioeconomic attributes) and people flows.

Conclusion Our findings support the conceptualisation of neighbourhood crime as an ecological network, rather than as purely neighbourhood-level or spatial phenomenon. The policy implication is that a focus on the violence levels in one neighbourhood may be insufficient to reduce its rates of violence if its position in the citywide network of crime connections is overlooked.

Keywords Neighbourhood violence · Crime diffusion · Network analysis · Exponential random graph models

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Introduction

We focus on the question of how crime trends in one neighbourhood spill-over into other neighbourhoods to create correlated trends in violent crime across a city. If we can understand what drives these citywide connections, we shall be a step closer to understanding what drives trends in violence at the state and national level. We argue that a more capacious and coherent model of crime diffusion is needed to understand what drives these correlations in crime trends, one that coherently draws together three key processes that have emerged in the quantitative criminology literature:

1. *Spatial contagion*: this approach focuses on correlation between the crime rates of contiguous or nearby areas (Graif et al. 2021, Loftin 1986, Fagan et al. 2007). Such correlations arise as a result of epidemic contagion effects, such as learned behaviour and violent retaliations between neighbouring gangs (Loeffler and Flaxman 2018; Morenoff et al. 2001; Tita and Ridgeway 2007; Papachristos 2009), and displacement effects – as police intervene to reduce crime in a particular hotspot it may cause violence and other offences to move "round the corner" (Weisburd et al. 2006). These processes suggest that crime will be more highly correlated between adjacent or nearby areas.
2. *Neighbourhood homophily*: this explanation posits that areas with similar criminogenic characteristics and vulnerabilities are more likely to be connected in terms of crime correlations. Graif et al. (2021) note that there is a "century old body of research on the role of socioeconomic disadvantage in increasing neighborhood crime." This strand of research shows how crime rates are "situated in the socioeconomic conditions of neighborhoods, as opposed to an individual problem rooted in individual morality" (Papachristos and Bastomski 2018). Note that neighbourhood homophily explanations do not rely on the spatial contiguity or proximity of neighbourhoods to motivate inter-neighbourhood crime linkages occurring.
3. *People Flows:* more recent research on urban violence has recognized the potential for linkages between people and communities to drive common patterns of violence across neighbourhoods (Papachristos and Bastomski 2018; Sampson and Levy 2020). Again, this explanation does not rely on the spatial proximity of neighbourhoods but on the strength of people flows between both near and distant neighbourhoods.

Note that these three explanations provide strong a priori reasons to expect inter-neighbourhood correlations in crime (e.g. between neighbourhoods that are in close proximity, or that have similar levels of deprivation, or that have notable people flows between them). Yet, studies that deploy these theories tend to use them as explanatory variables in traditional regression models (such as OLS or negative Binomial) of neighbourhood crime that assume conditional independence between each row of the data (i.e. each neighbourhood). Such models implicitly conceptualise crime within a neighbourhood as being mutually independent of crime in other neighbourhoods, even though all three theories of crime noted above point towards an ecological network conceptualisation of crime as being more appropriate.

Whilst Brazil et al.'s (2025) recent review charts the growing use of network methods to study neighbourhood crime, the studies reviewed use such methods to create network-based *explanatory variables* (cf Sampson and Levy's 2020 measure of "triple disadvantage"), rather than formulating the variable to be explained – the *dependent variable* – itself as a network variable. Adopting network-based dependent variables requires not only a conceptual shift towards fully embracing an ecological network approach to conceptualising neighbourhood crime, but also a move away from empirical methods that require conditional independence (where the errors are assumed to be independent across neighbourhoods).

Rather than thinking of spatial dependence, neighbourhood homophily and people flows as processes that explain crime rates in individual neighbourhoods, we propose thinking of them also as potential drivers of *city-wide networks of inter-neighbourhood crime correlations*. We argue that adopting an ecological network conceptualisation of the dependent variable aligns more coherently with Sampson's (2004, p. 158) notion that, "neighbourhoods are themselves nodes in a larger network of spatial relations." Our approach also coheres with recent empirical developments in the literature that emphasize the role of co-offending networks and people flows between neighborhoods. Such networks provide important conduits for the diffusion of interpersonal violence and potentially explain how rises and falls in violent crime emerge and cascade within and across cities and regions.

Having set out our conceptual framework, we offer an empirical application using Exponential Random Graph Models (ERGMs). Whilst ERGMs have been used to explain the factors that drive *individual*-level linkages such as co-offending ties (Papachristos and Bastomski 2018), they have not, as far as we are aware, been used to model *ecological* networks of crime, such as the inter-neighbourhood correlations in shooting incidents explored in this paper. Using ERGMs to model a network conceptualisation of crime avoids the restrictions imposed by the conditional independence assumption of standard regression models which essentially assume away the very linkages between neighbourhoods we are interested in. Unlike spatial dependence models (Graif et al. 2021) the ecological ERGM approach does not restrict crime connections between neighbourhoods to those in close proximity. Rather, spatial proximity is just one of a range of factors that can link together neighbourhoods with correlated trajectories of violence.

Drawing on a dataset of shootings in Chicago census tracts from 2014–2020, we create a network map of the links between nodes (neighbourhoods) where the edges denote high levels of correlation in neighbourhood gun violence. We attempt to explain this ecological network of gun violence by modelling it as the dependent variable in an ERGM. The explanatory variables in our model capture the three mechanisms described above to explain the ties between neighborhoods: (1) *spatial dependence* (Graif et al. 2021); (2) *neighbourhood homophily* share underlying characteristics associated with violence, such as concentrated poverty and high rates of residential mobility (Sampson et al. 1997); and (3) *people flows* between neighbourhoods (Levy et al. 2020).

Literature

The nature of violence in the United States has undergone massive changes in the past sixty years. The national violence rate began rising in the 1960 s and continued through the early 1990 s, before peaking in 1993 (Blumstein 1995; Cook and Laub 1998). Thereafter, the United States experienced a dramatic decrease in violence, with gun homicides down 40% by the end of 2000. This decline continued through the 2010 s ending in 2014. Since then, violence has surged dramatically, reaching its highest levels in the years since (Sharkey and Marsteller 2022).

These prolonged changes in national violence rates raise questions about how movements in violence spread across neighbourhoods and cities to create such pronounced country-wide trends. What are the micro-level processes underpinning the fall and rise of macro-level crime? Is violent crime diffusion largely a spatial phenomenon with changes in violence in one neighbourhood spilling over into adjacent neighbourhoods, cascading outwards like ripples in a pond? Or does the diffusion leap over swathes of neighbourhoods, driven by 'neighbourhood homophily' where linked trends in violence arise between even distant neighbourhoods because they have similar socioeconomic characteristics which means they are likely to respond in similar ways to external shocks? Or perhaps it is more about the physical movement of people between areas? Violence is committed by people against people. So, it is the flow of people between neighbourhoods that is the key medium of contagion, rather than physical distance or neighbourhood similarity per se.

The spatial explanation has received a lot of attention over the past twenty years. A considerable number of empirical studies have investigated violent crime (e.g., Cohen and Tita 1999; Morenoff et al. 2001; Tita and Cohen 2004; Ratcliffe and Rengert 2008, Braga et al. 2010) at various geographic levels, including the county level (e.g., Messner et al. 1999), the census tract level (e.g., Tita and Cohen 2004), and the block level (e.g., Ratcliffe and Rengert 2008). The upshot of these studies is that violence in America has notable geographical concentrations and exhibits spatiotemporal non-random clustering. Violence is typically concentrated, not only in specific neighborhoods, but also in specific locations within those neighbourhoods, often in a small fraction of micro-geographic units such as street segments. Weisburd et al. (2012), for example, found that fewer than 5% of street blocks in Seattle accounted for 50% of crimes.

These findings lead naturally to explanations of crime that conceive of inter-neighbourhood networks of crime as a purely spatial phenomenon. As such, there is no need to reconceptualise the dependent variable as a network-based phenomenon. Rather, C_i, the crime rate in each neighbourhood i, can be conceptualised as a function of the neighbourhood's attributes, A_i, and of C_j, the crime rate in adjacent neighbourhood(s) j, where j is adjacent (or in close proximity) to i:

$$C_i = f\left(C_j, A_i\right)$$

Using traditional regression to estimate this relationship overlooks the possibility that there may be factors other than spatial proximity that cause error term correlations to occur between the units of analysis (neighbourhoods). However, an influential body of work has emerged emphasizing the role of social networks between individuals as an underlying channel for violence propagation (Papachristos et al. 2015; Papachristos and Bastomski 2018) not restricted to geographical proximity. Violence in general, and shooting incidents in particular, are often retaliatory incidents connected to earlier violent crimes. Some contagion theories have examined the timescales and mechanisms in which violence cascades across space (Loeffler and Flaxman 2018), but the overall effect will be to generate potentially persistent inter-neighbourhood correlations in crime. Given the recent surge in gun violence afflicting many US cities (Braga et al. 2010, Sharkey and Marsteller 2022), and the retaliatory nature of gun shootings within disadvantaged social networks (Morenoff et al. 2001; Tita and Ridgeway 2007; Papachristos 2009), empirical research has been investigating whether or not the dynamics of these shootings, and the associated network linkages across neighbourhoods, could inform interventions aiming to reduce violence.

Whilst there is a growing body of evidence on relationship between violence and social networks between *individuals* (Blumstein and Rosenfeld 1998; Papachristos 2009; Papachristos et al. 2015; Short et al. 2014; Green et al. 2017), relatively little attention has been paid to explaining ecological correlations in shooting incidents – i.e. at the *neighborhood* level. The emphasis in the ecological crime diffusion literature remains on the role of contiguity and proximity. Both Peterson and Krivo (2009) and Tita and Greenbaum (2009), for example, find that crime rates are mirrored in proximate neighborhoods (see also Anselin et al. 2000; Anselin 2002; Graif et al. 2021; Morenoff et al. 2001).

However, spatial dependence alone does not explain why violence spreads out in certain directions but not others, besetting some neighborhoods while leaving others mostly unscathed. Social proximity, as well as spatial proximity, may promote criminogenic ties and the diffusion of crime. Social ties, such as friendship and business connections, will likely have a geographical dimension, but may also transcend spatial proximity.

Individuals can be socially connected with residents of distant areas through a variety of channels (Wellman 1999a; 1999b; Mears and Bhati 2006). ‘Homophily’, the human tendency to associate with like people, for example, means that people of similar social background and ethnicity may be more likely to form friendship ties (McPherson et al. 2001; Papachristos and Bastomski 2018) and this means that we may be more likely to see *neighbourhood homophily* in crime – stronger connections between neighbourhoods of similar socio-ethnic composition, even if these neighbourhoods are not contiguous. Social ties across neighbourhoods may manifest themselves in criminal behaviour, such as co-offending (Schaefer 2012, Papachristos and Bastomski 2018); but also in non-criminal activities, such as commuting (Graif et al. 2021), which in turn may make the emergence of criminal links between neighborhoods more likely. Indeed, the mobility and interconnectedness of urban life means that individuals may spend a significant proportion of their time on activities that occur outside their residential spaces—a fact that increases their exposure to other neighborhoods (Sampson and Levy 2020; Graif et al. 2021).

However, whilst individual-level crime networks and commuting flows have been introduced into ecological network models of crime (Brazil et al. 2025), their use so far been has been limited to creating explanatory variables for use in fairly traditional regression-based models of crime at the neighbourhood level, which retain the assumption of conditional independence between neighbourhoods. Essentially, these papers have used network methods to measure explanatory variables that capture non-spatial links between neighbourhoods, creating variables such as S_{ij}, the social proximity of neighbourhoods i and j. Such variables are then entered as covariates in models that explain C_i,

$$C_i = f\left(C_j, S_{ij}, A_i\right)$$

rather than to explain citywide networks of crime correlations between neighbourhoods (C_{ij}).

Papachristos and Bastomski (2018, for example, use an ERGM to model how “spatial and social distance between neighbourhoods contribute to the formation of co-arrest ties. However, when they estimate the effect on *neighbourhood* homicide rates, they do so by entering S_{ij} into a regression model which implicitly assumes conditional independence between neighbourhoods, other than those captured by their measures of social or spatial proximity. Similarly, Graif et al. (2021, p.348), argue that spillovers in crime between neighbourhoods may be, “observed between distant areas connected through routine commuting”. They create a measure of “network disadvantage” computed as the “weighted average of disadvantage levels in all work areas connected to it, where each weight is based on the strength of the commuting flow”. This variable is entered as an explanatory variable in negative binomial regressions that explain individual neighbourhood crime rates as a function of spatial dependence and commuting flows. Sampson and Levy (2020) adopt a similar approach, using network methods used to create measures of “triple disadvantage” based on people flows between deprived neighbourhoods that are entered as explanatory variables in standard regression models. Crucially, none of these models consider using network theory and methods to shape the way we frame the dependent variable in ecological models of crime.

An key motivation for adopting a neighbourhood-level network conceptualisation of the dependent variable is that there may be a plethora of processes and features that link areas other than geographical proximity. A *neighbourhood homophily* explanation, for example, would emphasise that neighborhoods can be connected to one another by similarity of socio-ethnic mix and life circumstances that transcend physical distance. Indeed, neighborhood-based socioeconomic disadvantage, including poverty, unemployment, inequality, and segregation have emerged as key predictors of violence (Peterson and Krivo 1993; Morenoff et al. 2001; Weisburd et al. 2012). Housing conditions, concentrated poverty and racial segregation, and disinvestment in communities have also been strong predictors (Sharkey and Marsteller 2022; Harding 2010; Sampson et al. 1997). Racial disparities intersect with all these factors, especially in the US context. Sharkey (2014), for example, found that 87% of predominantly Black neighborhoods and 83% of predominantly Hispanic neighborhoods suffered from significant socioeconomic disadvantage and were, in many cases, surrounded by disadvantaged neighborhoods. In contrast, only 15% of the predominantly white neighborhoods suffered from local or proximate disadvantage.

It seems reasonable, then, to expect crime rates in neighborhoods facing similar life circumstances will adjust to external shocks in similar ways. Events that affect any of these socioeconomic drivers of violent crime (such as economic downturns, changes to public policy, or racially contentious incidents) will likely have more comparable effects on crime rates in similar neighborhoods compared with dissimilar ones. Relaxing the assumptions of conditional independence between neighbourhood crime rates seems to be an obvious implication of neighbourhood homophily.

Recent research has linked intra-community settings with mechanisms that promote co-offending (Schaefer 2012, Papachristos and Bastomski 2018), gang conflicts (Papachristos et al. 2013), residential instability (Sampson and Sharkey 2008), and commuting to work (Graif et al. 2021) only adds to this imperative. We propose moving away from a reliance on conceptualisations that emphasise individual neighbourhood crime levels as the variable to be explained towards frameworks that focus on explaining the citywide networks of inter-neighbourhood correlations in crime. Family and workplace relationships, along with resources and institutions including education institutes, childcare centres, and city parks, bring together people from various residential areas and, thus, increase the flows of people across neighborhoods (Small and McDermott 2006; Murphy and Wallace 2010; Tran et al. 2013). Both public transportation and commercial commuting influence the daily flows and the routine activities of various groups of people (Graif et al. 2021). All of these people flows have the potential to link trends in criminal activity across neighborhoods. Graif et al. (2021), for example, examined both workplace commuting and exposure to workplaces in disadvantaged neighborhoods, but did not consider the mobility of individuals or the role of inter-neighborhood movement in violence rates. A handful of studies have examined the impact that commuting flows can have on patterns of crime diffusion.

In summary, studies that focus on spatial proximity as the principal conduit for violence diffusion across neighborhoods neglect important social interactions capable of mirroring and inducing social phenomena between distant neighbourhoods (Papachristos and Bastomski 2018). Such studies also suffer from a methodological weakness: an over-reliance on OLS and other regression methods which either assume independence between neighbourhoods (where neighborhoods are observations in the regression, and therefore assumed to be unrelated), or only allow for very limited and specific forms of inter-neighbourhood dependence (e.g. by allowing for dependence between neighborhoods that are contiguous or in close proximity, defined in terms of very particular functional forms; Anselin et al. 2000; Morenoff et al. 2001; Kirk 2009; Sampson 2012; Crowder and South 2011; Peterson and Krivo 2010; Vogel and South 2016).

We do not doubt the importance of spatial proximity which has been a consistent finding in the crime-diffusion literature (e.g. Zeoli et al. 2014). The problem is that such models assume distant neighborhoods to be unconnected. We argue that is a symptom of a more fundamental flaw in both conceptualization and empirical research design. Regression analysis works well for modeling relationships between *variables*, but it is simply the wrong approach if the goal is to understand the links between *observations* (‘nodes’; in our case, neighbourhoods). If we are interested in the connections between observations, such as the factors that cause neighbourhoods to be linked in some way, then we need a network conceptualisation of the dependent variable that does not exclude the very correlations we are seeking to explain. We need a form of analysis which places no limits on which pairs of observations (i.e. neighborhoods) can be connected.

Whilst network models have been applied to co-offending between individuals, they have not been applied to crime diffusion at the neighbourhood level. This is surprising as such models are in some ways an obvious choice. So, although neighbourhood-level network models have, for example, been used to research house price dynamics (Dean and Pryce 2017), a thoroughgoing network approach to both conceptualization and empirical estimation has yet to be applied to ecological crime diffusion and the co-movement of neighborhood level violence. When social network methods have been applied by criminologists, they have tended to focus on networks of individuals, rather than networks of neighborhoods. Schaefer (2012), for example, studied individual-level co-offending networks in Maricopa County, Arizona, and uncovered evidence that social proximity contributes to the structure of criminogenic networks. More specifically, he found that neighborhoods with similar demographic characteristics are more likely to share co-offending ties than demographically disparate neighborhoods. Similarly, Papachristos and Bastomski (2018) examined how criminal co-offending forges connections between various neighborhoods in Chicago.

Whilst these individual-level results confirm that spatial proximity is important for the phenomenon of linked neighborhoods, they also found that co-offending ties are common between socially similar neighborhoods, irrespective of the distance between them. Relatedly, Mears and Bhati (2006) investigation into violence diffusion across Chicago neighborhoods found that local neighborhood deprivation is a strong predictor of violence in socially proximate communities.

This focus in the criminology literature on networks between individual offenders mirrors the emergence of social network research more generally, which had its origins in the study of interpersonal relationships. However, network analysis has since broadened enormously to consider all manner of linkable entities, including links between geographical units such as countries (e.g. Smith and White's 1992 network study of trade flows) and, indeed, neighborhoods (e.g. Dean and Pryce's 2017 network study of co-movements in neighborhood house price dynamics). So, whilst studies of co-offending networks have yielded important insights, there is no reason to limit network analysis to individual-level connections. When a pair of neighbourhoods have crime rates that move in tandem, we can think of them as being connected nodes in a wider network of crime diffusion. In the same way that Dean and Pryce (2017) applied network methods to study the co-movement of house prices across neighborhoods, we aim to show how crime diffusion can also be conceptualized as a network, focusing on what determines the correlations in crime between neighborhoods.

Conceptual Framework

In contrast to existing neighbourhood ecological approaches (Brazil et al. 2025), we propose conceptualising the dependent variable as C_{ij}, a network-based representation of inter-neighbourhood crime linkages. In this framing of the crime diffusion conundrum, neighbourhood crime dynamics are conceived as a network, where the nodes represent neighbourhoods, and dyads (links between pairs of nodes) represent inter-neighbourhood correlations in crime. The dyads therefore occur when the incidence of gun violence follows remarkably similar trajectories over time in a pair of neighbourhoods. The likelihood that any two neighbourhoods are linked in terms of similarity of crime dynamics is the phenomenon to be explained. Spatial contiguity, similarity of neighborhood characteristics, and movement flows are the main explanatory variables that we use to predict shooting ties between neighborhoods:

$$C_{ij} = f\left(D_{ij}, A_i, S_{ij}\right),$$

where D_{ij} = euclidean distance between neighbourhoods i and j; A_{ij} = difference in attributes of i and j, and S_{ij} = the social connection between i and j (e.g. captured by the strength of commuting flow between them, as in Graif et al. 2021).

The network conceptualisation of the dependent variable, we argue, provides us with a powerful way for thinking about crime diffusion and how to coherently incorporate the two important themes that emerge from the literature discussed above. First, neighborhoods are not isolated islands. Rather, they are connected to each other through various mechanisms, such as those related to co-offending, commuting, and gang conflicts. Second, both urban mobility and social interconnectedness increase the exposure of individuals to other areas within the city. Moreover, this network conceptualization enables us to readily incorporate other dyadic variables – factors that link neighbourhoods, such as flows of people—as explanatory variables. Although the existing research on neighborhood networks has examined a host of mechanisms that connect neighborhoods to one another and that affect citywide commuting patterns, how a mobility-based network affects the ecological dynamics of violence over time remains unknown. Previous studies have provided evidence about the impact of certain types of commuting flows (e.g., work commuting (Graif et al. 2021)) on local crime rates, but we are aware of no studies that conceptualise the dependent variable in an ecological network of crime correlations.

Our core research question is whether inter-neighborhood correlations in crime rates arise because of distance-based factors that link criminogenic behaviour across space, represented in Fig. 1 panel (i); because they have similar population characteristics (i.e. neighbourhood homophily drivers of crime) as represented in panel (ii); or because they are linking people together through direct interactions (i.e. people flows) as represented in Fig. 1 panel (iii).

1. *Spatial proximity:* The form of dependence is shown graphically in the map of stylized neighborhood depicted in Fig. 1 panel (i), where the dots are neighborhood centroids – the nodes in our network, and the links between nodes represent co-movement of crime rates between a pair of neighborhoods. The idea of spatial dependence is shown by the links between neighborhood A and its contiguous neighbors, B, C and D. Alternatively, spatial dependence can be defined in terms of geographical distance with the closest neighborhoods having the strongest levels of co-dependence in terms of crime trajectories. The theoretical rationale for this approach is Tobler's First Law of Geography: 'everything is related to everything else, but near things are more related than distant things' (Tobler 1970, p.236). This has been borne out in the crime distribution literature which has shown that contiguity/spatial proximity is a crucial factor in explaining crime distribution. Crime rates in one neighborhood are influenced by crime rates in surrounding neighborhoods (e.g., Morenoff et al. 2001; Zeoli et al. 2014). In particular, previous studies indicating that disadvantage in geographically proximate neighborhoods affects—or at least is very significantly associated with—crime rates and victimization

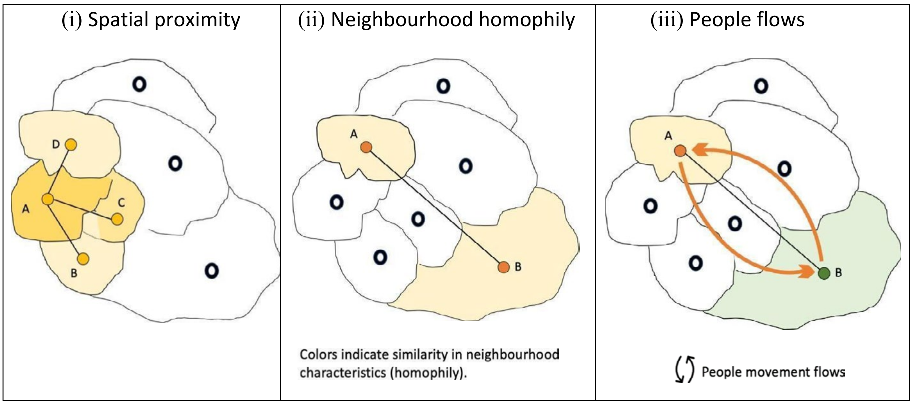

Fig. 1 Conceptual framework

in proximate neighborhoods (Morenoff et al. 2001, Peterson and Krivo 2009, Peterson and Krivo 2010, Crowder and South 2011, Vogel and South 2016). These findings are also in line with a previous study showing that crime rates may be affected by poverty in proximate neighborhoods (Graif et al. 2017). Thus, in the Chicago data, we should expect crime co-movement links are more likely to be formed between proximate neighborhoods.

2. *Neighbourhood homophily (social proximity):* In the network analysis literature, the tendency for nodes to be more likely to form ties with similar nodes is described as "assortative mixing" or "homophily". This tendency has been widely observed across a range of phenomenon including trade flow links between countries (Zhou 2011), neighbourhood-level house price dynamics (Dean and Pryce 2017), individual-level friendship connections (McPherson et al. 2001); and even at the cellular level in terms of synapse connections between similar neuron clusters (Teller et al. 2014). In the context of crime dynamics, we are not aware of any previous studies that test for homophily in crime trends at the neighbourhood level. Nevertheless, as noted in our literature review above, there are good a priori reasons to expect neighbourhood crime rates to be more likely to move in tandem when those neighborhoods are similar in socioeconomic characteristics, especially those associated with crime. We represent this visually in Fig. 9 panel (ii), where neighborhoods A and B are similar in important characteristics and are therefore more likely to be connected in terms of co-movements of shooting incidents, even if they are not geographically contiguous. The same node color indicates a similarity between neighborhood A and B in terms of their attributes (e.g., demographic, socioeconomic, etc.).
3. *People flows:* Understanding the relationship between the flows of people across neighborhood and the co-movement of violence is important for several reasons. First, higher movement flows among people travelling between two neighborhoods are associated with increases in the potential of inter-neighborhood social-tie formation (Sampson and Levy 2020). A previous study in Chicago by Sampson (2012) provided evidence that social ties affect residential choices, because people seeking a home tend to move to a neighborhood where they had prior social connections. Furthermore, prior research found that such social ties (1) require social interactions across neighborhoods, a phenomenon that relies on the movement of information between neighborhoods (Sampson and Levy 2020), and (2) increase the likelihood of co-offending networks (Papachristos and Bastomski 2018, Schaefer 2012). Second, this movement of people can shape the movement of information, attitudes, cultural practices, and beliefs across neighborhoods, resulting in changes that are mirrored in the city as a whole (Sampson and Levy 2020). By conceptualizing the city as a network of neighborhoods, researchers can better understand the dynamics of violence and, in particular, how social issues (e.g., racial segregation, concentrated poverty) affect individuals' mobility and, in turn, may help to understand the co-movement of violence. As shown in Fig. 1 panel (iii), neighborhoods A and B are not contiguous, but experienced higher people flows between them and therefore are likely to be connected in terms of co-movements of shooting incidents. The arrows indicate movement flows between neighborhood A and B. Thus, the higher the movement flows between neighborhood A and B, the more likely neighborhoods A and B are to be connected in terms of co-movement of crime.

Methods

As noted above, traditional statistical methods such as regression models are ill-suited for exploring the co-movement of neighbourhood crime and the factors that connect neighbourhoods because they assume that each unit of observation (i.e., each neighborhood) is independent from all others, other than the effect of proximity. This assumption is clearly problematic—it precludes the very phenomenon we are seeking to study. Using a network-based approach leads us naturally to adopt statistical network methods specifically designed for analysing ties between nodes and the factors (such as node attributes, and other dimensions of node linkage) that drive them.

Exponential Random Graph Modeling

Let $G(V, E)$ be an undirected network, where V is the set of neighborhoods in the city and E is the set of edges. The links between neighborhoods can be summarized with a binary adjacency matrix, **C**, the elements of which = 1 if there is a high pairwise correlation in shooting incidents over time between node i and node j, and = 0 otherwise. So an edge is said to exist between i and j if the correlation in shooting incidents, C_{ij}, is greater than N, the selected threshold for high correlation. Exponential random graph models (ERGMs) provide a powerful framework for exploring the factors that determine network variables such as **C** that measure tie formation between nodes. The basic ERGM takes the form:

$$pr\left(X = x\right) = \left(\frac{1}{k}\right) exp\left\{\sum_{A} \eta_A g_A\left(x\right)\right\}$$

The model specifies the probability of a set of ties, X, for all possible nodes with node features, dyad attributes, and observed network statistics (Lusher et al., 2013; Robins et al., 2007). g_A is a vector of network statistics, η_A is a vector of corresponding coefficients, and A indexes multiple statistics in $g(x)$. The variable k is a normalizing constant for the distribution. ERGM packages in R were used for all models (Hunter et al., 2008).

ERGMs are useful because they allow us to explore the link between the network dependent variable of interest (whether a pair of nodes are linked in some way) and a list of potential explanatory variables that can include a combination of both node-specific measures such as neighbourhood deprivation, and network variables which measure directly the difference or connections between nodes (such as difference in the poverty rate between i and j, or flows of people between i and j). Note that in standard regression models such network measures cannot be included either as dependent variables or as explanatory variables without condensing them to vector format, which potentially loses important information. In our model, nodes (neighbourhoods) are linked if they have highly correlated trends in shooting incidents over time. This matrix of correlations forms the dependent variable. To explain this network inter-neighbourhood correlations in shooting incidents we include shared underlying neighbourhood characteristics associated with violence: geographical proximity, differences in neighbourhood attributes, and people flows between neighbourhoods.

As well as the list of potential explanatory variables, our ERGM also includes an "Edges" term on the right hand side. This is analogous to an intercept in a traditional regression model. It captures the baseline probability of any two nodes (in our case, neighborhoods) being connected, i.e., forming a tie in terms of co-movement of shooting incidents. By including this term, we control for the overall density of the network, ensuring that the other predictors are measured against this baseline probability of tie formation. In other words, the edges term is included to account for the baseline probability of tie formation in the network, independent of other predictors. It helps model the overall network density—the general tendency for neighborhoods to form connections in the co-movement of crime trends.

A negative coefficient for edges (which the results show) means that, in general, ties between neighborhoods (co-movement in violence) are less common than random chance would suggest. This indicates that violence co-movement is structured and driven by specific factors rather than occurring at random.

Data

Study Area

This study uses data on the city of Chicago, the largest city in the state of Illinois and the third most populous city in the United States with over 2.7 million residents. Data on shootings are measured at the levels of census tracts and are from the American Violence Project, a repository of data on violence in the largest U.S. (Sharkey 2023). The data cover annual shooting incidents in each census tract in Chicago between 2014 and 2020. A census tract is an area established by the US Census Bureau as roughly equal to a neighborhood, the population of which typically ranges between 1,200 and 8,000 residents. Census tracts have been used to represent neighborhoods in many ecological studies of crime (e.g., Krivo and Peterson 1996; Morenoff and Sampson 1997; Peterson et al. 2000). For the city of Chicago, there are 833 census tracts, 731 of which were included in the present study (with the remainder excluded owing to their insufficient data).

Dependent Variable

The variable we seek to explain is the citywide network of inter-neighbourhood correlations in shooting incidents in Chicago over the period 2014–2020. Our dependent variable is therefore a network variable made up of binary links between neighborhoods. The variable equals 1 if shooting incidents between a pair of neighbourhoods is highly correlated – i.e. greater than 0.9, and 0 otherwise, over the study period. We selected the correlation threshold of 0.90 after carefully assessing the stability of model coefficients across various threshold values. Initially, we tested thresholds ranging from 0.50 upwards, incrementally increasing this threshold to observe how it impacted ERGM coefficients and overall model stability. Stability was defined as the range of threshold values for which model coefficients remained substantively consistent in terms of magnitude, direction, and significance. Stability in model results was found within the 0.50–0.90 threshold range. We selected the threshold of 0.90 as our final choice because it ensured that ties reflected significant correlations in violence, whilst also producing stable coefficients.

Table 1 Census tract descriptive statistics ($N=731$)

	Median	Mean	St. Dev
Poverty	19.30	21.46	14.87
Percent Black	13.77	39.50	41.14
Percent Hispanic	12.95	27.21	30.13
Resident instability	59.40	56.74	20.09
Youth population	14.40	14.92	6.85
Older population	20.40	21.12	8.35
Total population	3177	3463	1800

Explanatory Variables

Our covariates include several measures of neighborhood characteristics from US census data (2014), described in Table 1: *(1) poverty rate,* which designates the percentage of families whose incomes are below the poverty line; *(2) percent Black*, which designates the percentage of residents who are Black/African American; *(3) percent Hispanic,* which designates the percentage of residents who are Hispanic; *(4) residential instability*, which is based on the percentage of households that moved to the given neighborhood after 2010 and the percentage of housing that is renter-occupied (we standardized each of the indicators, summed the resulting z-scores, and then divided these sums by the number of indicators in order to construct each scale); *(5) youth population:* which designates the population aged 10–17. *(6) older people*, i.e. aged 55+. *(7) spatial proximity*, which refers to the geographic distance, measured in miles, between neighborhood centroids; and *(8) people-mobility flows* obtained from SafeGraph (SafeGraph.com),[1] which are calculated on the basis of millions of anonymous mobile phone users' visit trajectories to various places.[2]

To measure flows of mobility across Chicago census tracts we utilize mobility data from SafeGraph's 2019 "Social Distancing Metrics" dataset to construct flows of mobility across census tracts in Chicago. The dataset tracks daily mobility patterns based on GPS data from roughly 40 million mobile devices across the United States, representing between 5 and 10% of the U.S. population. The data originate from anonymized GPS signals collected via smartphone apps and Software Development Kits (SDKs), with location sharing enabled through explicit user consent. To ensure privacy, SafeGraph aggregates these signals at the census block group (CBG) level, reporting daily counts of movements from a given "origin" CBG to various "destination" CBGs. SafeGraph excludes any block group with five or fewer devices to further protect user privacy.

Safegraph data have been used in a growing body of research examining the segregation of flows of movement, exposure to areas of advantage and disadvantage, and the degree to which areas of a city are connected to each other (among other topics) (see Brazil et al. 2025 for an early review of this literature using Safegraph and other data). Like other forms of data attempting to capture mobility across the neighborhoods of a city, the use of

[1] From SafeGraph, a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places, via the SafeGraph Community. To enhance privacy, SafeGraph excludes census block group information if fewer than two devices visited an establishment in a month from a given census block group.

[2] The mobility data were computed, aggregated, and inferred the daily dynamic origin-to-destination (O-D) population flows at the census-tract level, and then trimmed the flows down to pairs consisting of at least 10 daily trips on average. The data were aggregated for 2019, which served as the annual base.

smartphone mobility data introduces several potential biases and limitations. Key concerns include disparities in smartphone ownership, uneven patterns of opting into location services, variability in app usage, and differential engagement with apps across demographic groups (Coston et al. 2021).

Prior research indicates that at the county level, SafeGraph's mobility panel aligns well with Census demographic characteristics (Squire 2019a, b). However, similar to all tract-level analyses using the data from Safegraph (Brazil et al. 2024; Cheng et al. 2025), we lack individual-level demographic data for device owners and detailed app opt-in rates, limiting our capacity to directly assess representativeness at the device level. Consequently, our analysis relies on the assumption that individuals who travel from a neighborhood are demographically representative of the neighborhood's entire population (Cheng et al. 2025).

Despite widespread smartphone ownership in the U.S.—exceeding 80% of Americans by 2019, a significant increase from 35% in 2011 (Pew Research Center 2024)—we cannot verify demographic representativeness of location opt-ins without individual-level data. The ubiquitous use of third-party location services across mobile applications (Chitkara et al. 2017) implies broad yet potentially uneven coverage. Although SafeGraph does not disclose specific apps or demographic details of its device users, prevailing research suggests extensive reliance on generic software development libraries (SDKs) for location data collection (Pybus & Coté, 2024; Cheng et al. 2025).

To address potential bias, we implement a "post-hoc stratification reweighting" correction recommended by Squire (2019a). Similar to survey reweighting techniques, this method adjusts daily device counts at the block-group level to reflect accurate population distributions as reported in ACS data. Although this approach improves aggregate trip volume accuracy, it does not fully resolve biases arising from individual-level device sampling. Next, we aggregate the block-group-level data up to the census tract level to match our outcome variables' spatial scale. We remove trips originating and ending within the same census tract, as well as trips crossing the boundaries of the city limits.

Estimation Strategy

We estimated a series of ERGMs in order to identify factors that predict the probability that two neighborhoods are linked to each other through common trends in violence. We focus our attention on movement flows, social distance, and spatial proximity. The measurement of movement flows is constructed by calculating the average annual trips from origin to destination census tracts in 2019 within the Chicago commuting zone. Social distance is the extent of dissimilarity between neighborhoods in terms of poverty level, the Black segment of the population, the Hispanic segment of the population, residential instability, and age composition. Social distance was measured by calculating the absolute differences between the neighborhood characteristics for all possible dyads in the network. Spatial proximity is computed as the number of miles between neighborhood centroids.

The exponential graph models were estimated as follows. The first model was estimated as a baseline model to examine how a neighborhood's features were associated with crime co- movement ties to other neighborhoods, but not for examining the effects of movement flows, social distance, or spatial distance. Next, we add measures of spatial and social distance to the model, and then in a third model we add movement flows. We use the Akaike Information Criterion (AIC; Akaike 1974) to assess the improvement in models to determine the contribution of each dimension to explain he structure of the network. Based on information theory, the AIC measures the information loss associated with model estimation, and guards against overfitting by penalizing models that have too many parameters. The lower the AIC, the lower the information loss, and the better the model.

Results

Table 2 presents the ERGM results regarding the three core factors that explain the formation of shooting-incident co-movement ties between neighborhoods: (i) spatial proximity; (ii) neighbourhood homophily and (iii) people flows. The baseline model, Model 1,

Table 2 ERGM Coefficients and standard errors

	Model1	model 2	model 3	Model 4
	B (SE)	B (SE)	B (SE)	B (SE)
Edges	−4.52*** (0.01)	−4.14*** (0.06)	−4.23*** (0.06)	−4.33*** (0.07)
Neighbourhood characteristics				
% Poverty	0.01 (0.02)	0.04 (0.02)	0.04 (0.03)	0.03 (0.02)
% Black	−0.16*** (0.03)	−0.17*** (0.03)	−0.16* (0.03)	−0.17*** (0.03)
% Hispanic	−0.14*** (0.01)	−0.19*** (0.02)	−0.18*** (0.02)	−0.18*** (0.02)
Residential Instability	0.05** (0.02)	0.03 (0.01)	0.03 (0.02)	0.03* (0.01)
% Age 15–24	0.06*** (0.01)	0.10*** (0.01)	0.11*** (0.01)	0.10*** (0.01)
% Age 55 and over	0.04* (0.01)	0.03* (0.02)	0.03* (0.02)	0.03 (0.02)
Spatial distance				
Geographic distance		−0.11*** (0.02)	−0.08** (0.03)	−0.03 (0.03)
Neighbourhood homophily				
% Poverty		−0.05* (0.03)	−0.05 (0.03)	−0.04 (0.02)
% Black		−0.08** (0.02)	−0.08** (0.03)	−0.09** (0.03)
% Hispanic		0.04 (0.02)	0.04 (0.03)	0.04 (0.03)
Residential Instability		−0.02 (0.02)	−0.02 (0.02)	−0.03 (0.02)
% Age 15–24		−0.10*** (0.02)	−0.10*** (0.02)	−0.10*** (0.02)
% Age 55 and over		0.05* (0.02)	0.05** (0.02)	0.06** (0.02)
People flows				
People flows			0.02*** (0.03)	0.02** (0.01)
AIC	30904	30834	30822	30543

excludes these three core drivers, and includes only the characteristics of neighborhoods. That is, it excludes the distance between neighbourhoods, the neighbourhood similarity variables (the difference between each pair of neighbourhoods in characteristics expected to be associated with the formation of shooting-incident co-movement ties) and the people flows. So, for each neighborhood, Model 1 includes only node-level covariates for poverty, percent Black, percent Hispanic, residential instability, and age composition. As shown in Table 2, neighborhoods whose populations had a high proportion of Black or Hispanic residents were less likely to display crime co-movement ties than were neighborhoods in which those demographic groups accounted for a small percentage of the population. By contrast, the higher the proportion of youths in a neighborhood's population, the higher the probability of crime co-movement ties in the neighborhood. In Model 1, the edges term is negative, which is normal in ERGMs and shows that, overall, ties were less likely to exist than not exist in this network.

Model 2 also excludes the third element (people flows) in our approach but includes the first two (spatial proximity and neighbourhood homophily). The model confirms the role of spatial proximity in tie formation: greater distance between neighborhoods reduces the likelihood of their crime co-movement ties.

To capture the neighbourhood homophily effect, we include edge covariates that measure the similarity of neighbourhood attributes between each pair of neighbourhoods. Including these in the model enables us to test for neighbourhood homophily by estimating the influence of neighbourhood similarity on the likelihood of violence co-movement ties forming between each neighbourhood dyad. These variables were calculated as the absolute difference between each pair of neighborhoods with respect: to the levels of poverty in each neighborhood, the percentage of Black and Hispanic in each neighborhood, the residential instability of each neighborhood, and the age composition of each neighborhood. As shown in Table 2, these three measures of social distance were significantly and negatively associated with the formation of ties between neighborhoods— the greater the differences, the weaker the probability of ties. This suggests that neighborhood homophily plays an important role in predicting whether trends in violence are similar in two neighborhoods. By contrast, neighborhoods with similar levels of seniors in the population were less likely to be connected to each other than were neighborhoods with contrasting levels of seniors. Overall, Model 2 performed better than the baseline model, yielding better AIC results. This suggests that that neighbourhood homophily and spatial proximity both help explain connections in neighbourhood violent crime dynamics.

Model 3 incorporates all three categories of crime determinants (spatial persistence, neighbourhood homophily, and people flows). It differs from Model 2 only in that it also includes the measure of flows of people moving from one neighborhood to another. The association was found to be significantly positive, indicating that the movement flows between neighborhoods increase the likelihood that a pair of neighborhoods are connected to each other by similar trends in shootings.

Model 4 includes the same variables as Model 3, but only for non-contiguous neighborhoods. The purpose of this model was to determine whether or not the results of the previous models were driven largely or even exclusively by the close proximity of neighborhoods. The results of Model 4 are similar to the first three models, but poverty and spatial-distance were no longer significantly associated with the formation of inter-neighborhood ties.

Taken together, the results of the four models appear to confirm our approach. Spatial proximity, socio-demographic similarity, and people flows all increase the likelihood that a pair of neighborhoods will be linked through common trends in violence. Neighborhoods close in proximity to each other, where people are moving back and forth, and with similar percentages of Black residents and residents under the age of 18 had similar trends in shootings.

As an additional robustness check, we removed ties to adjacent tracts as a way to verify that our findings are not driven purely by patterns of movement and violence in adjacent neighborhoods within Chicago. When we did this (Model 4), we found that spatial distance between tracts was no longer a strong predictor of ties (understandably), but neighbourhood homophily and flows of movement continued to be strong predictors of similar trends in violence. Hence, trends in neighborhood violence move together in part because of spatial proximity, in part because they have similar composition, and in part because the movement of people helps tie neighborhood trajectories of violence together.

Conclusion

We have sought to shed light on the conundrum of how neighbourhood-level processes drive macro-level dynamics in violent crime. We have focused in particular on the question of how trends in one neighbourhood spill-over into other ones to create linked trends in violent crime across multiple areas. We have argued that a more capacious model of crime diffusion is needed to explore this conundrum, one that brings together the three key processes that have emerged in the literature: (1) *spatial contagion*; (2) *neighbourhood homophily*; and (3) *people flows* in a coherent way. We have suggested that thinking about crime diffusion in terms of an ecological an ecological network conceptualisation of the dependent variable is more consistent with these three processes, each of which imply correlations in crime rates between neighbourhoods. Estimation based on explaining dependent variables that treat neighbourhoods as unconnected nodes (such as traditional regression models of neighborhood crime), rather than the networks of crime correlations between neighbourhoods, are at odds with these three processes and with the shift in the literature towards viewing neighbourhoods as nodes in larger networks of criminogenic relations.

This approach to conceptual framing and statistical analysis helps address a significant methodological shortcoming in much of the existing literature. Prior research has emphasized the spatial clustering of violence and the similarity and stability of violence trajectories over time in spatial units such as street segments and neighbourhoods. This strand of research has relied heavily on regression analysis, which assumes independence between observations (i.e. neighborhoods), or permits only specific forms of linkage (such as spatial correlation). The conditional independence assumption underpinning conventional regression models is clearly problematic as it precludes the existence of other types of linkage between neighbourhoods, including neighbourhood homophily and people flows, which are potentially core drivers of violence diffusion. Clearly, spatial dependence alone is insufficient to explain how linked crime trends emerge. For example, it does not explain why violence spreads out in certain directions but not others, besetting some neighborhoods while leaving others mostly unscathed. Also, it is at odds with recent analysis of co-offending networks at the individual level (Schaefer 2012, Papachristos and Bastomski 2018) which reveals *social proximity* to be a potentially important factor connecting neighborhood crime dynamics.

Using a network conceptualisation of the dependent variable requires a different type of empirical estimation, one that allows the dependent variable to be a matrix of neighbourhood linkages rather than a vector of neighbourhood crime levels. Exponential Random Graph Models (ERGMs) are designed for this very purpose. They are a class of statistical network analysis that allow for both network-based dependent variables and network-based explanatory variables that can accommodate a plurality of inter-neighborhood linkages. The method relaxes also entirely the conditional independence assumption.

We used ERGMs to estimate a model of ecological correlations in shooting incidents between neighbourhoods in Chicago as a function of: (1) spatial contagion; (2) neighbourhood homophily; and (3) people flows. Our results suggest that geographical proximity of neighbourhoods increases the likelihood of linked crime trends between neighbourhoods, as does social proximity (the similarity of neighbourhood characteristics), and the flow of people between neighborhoods. That is, the greater the flow of people across neighborhoods, the more likely it will be that shooting-incident ties will take shape across the neighborhoods. As an additional robustness check, we re-estimated the model with ties between bordering neighborhoods removed to demonstrate whether there is a persistent positive impact of the movement flows on the shooting dynamics independent of spatial contiguity. We found that people's movement flows did indeed remain positively associated with the probability of shooting incident ties between neighbourhoods, even without the contiguity variable. These findings substantiate the claim that close spatial proximity between neighborhoods is insufficient to explain the dynamics of violence across neighborhoods dynamics.

There are various possible explanations for this finding. For instance, commercial land use and other resources influence individuals' daily movements across an urban landscape. The lack of resources in disadvantaged areas affects residents' interactions with one another and residents' exposure to other areas, thus entailing the spread of criminal behavior to other neighborhoods. Another plausible explanation is that high-risk places such as illegal-drug markets and liquor stores could stoke aggression and promote criminal behaviors in people who frequent these sites but who live in another neighborhood. This explanation is consistent with the study by Peterson et al. (2000), which found that bars in local and contiguous neighborhoods were associated with elevated rates of violent crime in neighborhoods. Likewise, Groff and Lockwood (2014) reported that bars and subway stops were positively associated with violent crime and property crime in both local and distant areas within a city's limits. Another possibility is that the positive association between movement flows and the co-movement of violent crime is a function of criminals' commuting between each other's residential neighborhoods.

In addition to confirming the importance of spatial dependence and people flows in explaining violence diffusion, our results also provide strong evidence to support the *neighbourhood homophily* hypothesis – that similarity in underlying neighborhood characteristics associated with crime, increase the probability of shooting ties. In particular, similarity in poverty levels and in the Black and youth segments of a population, significantly increase the likelihood that shooting-incident ties will form between neighborhoods. These ecological findings are consistent with mechanisms that previous research discussed in relation to co-offending networks. For instance, homophily at the individual level increases the likelihood that criminals residing in spatially different—but demographically similar—neighborhoods will establish various relationships with one another, thereby promoting criminal activity that a non-resident of a neighborhood carries out in that neighborhood. Recent research based on individual-level social networks confirms this – similarity in socioeconomic characteristics has been found to increase the likelihood of criminal connections between neighborhoods (Schaefer 2012, Papachristos and Bastomski 2018).

Another possible explanation for these results is the retaliatory nature of gun shootings among adversarial social networks that span multiple disadvantaged neighborhoods (Morenoff et al. 2001; Tita and Ridgeway 2007; Papachristos 2009). Of course, both racial segregation (Morenoff et al. 2001) and poverty (Sharkey and Marsteller 2022) exist in many Chicago neighborhoods, and racial segregation in particular is strongly associated with the incidence of crime: Peterson and Krivo (2010) observed just such an association between inequality and violence rates in, where violence rates in predominantly Black neighborhoods were 327% higher than in predominantly white neighborhoods. Sharkey (2014) found that socioeconomic disadvantage was concentrated in 87% of the Black neighborhoods. In contrast, only 15% of the white neighborhoods suffered from local or proximate disadvantage. Also, in a recent study, Sampson and Levy (2020) provided suggestive evidence for the impact of such disadvantaged connectedness on the homicide and violence rate in Chicago.

This research has limitations. Whilst the findings confirms that Chicago's citywide network of crime correlations is related to: (1) spatial contagion, (2) neighbourhood homophily, and (3) people flows – it is difficult to be certain about the precise nature and the extent of these associations, largely because both the data and the methods used in this study have their own limitations. We acknowledge the need for consilience – complementary methodological approaches, such as qualitative or ethnographic methods, that will flesh out the meaning of our findings, and shed light on how the precise ways geographical proximity, neighbourhood homophily and movement flows give rise to linked crime trends across neighbourhoods (Papachristos and Bastomski 2018).

Future quantitative research could also explore in more detail the role played by people flows. Our analysis of people's movement flows was restricted by the limited availability and extent of the data. Thus, we included in this study only data on movement from 2019. Future work could make use of community survey data to provide a replication test of our findings. Also, exploring the effect of using a shorter timeframe of both shooting incident trajectories and movement flows might be a very valuable resource for understanding spatial and temporal patterns of violence. Not that we have assumed that people flows affect linkages in crime rates between neighbourhoods but it's possible that the direction of causation runs the other way – e.g. violent crime may itself affect inter-neighbourhood commuting (Graif et al. 2017). Emerging causal inference methods for ERGMs, such as the Bayesian approach proposed by Clark and Handcock (2024) may potentially offer ways to identify the direction of causation for these and other effects described in our model.

There are various other ways the ERGMs presented here could be extended. Value ERGMS, which allow the relationship between nodes to vary in magnitude, could be a useful extension. They would, for example, allow researchers to use the value of the correlation coefficient for inter-neighbourhood crime, rather than a binary measure indicating whether the correlation exceeds a given threshold. Note, however, that the number of possible configurations grows exponentially in value networks compared with binary ones so this can make estimation infeasible in larger networks. Stochastic Actor-Oriented Models (SAOMs) could also be used to explicitly model tie formation and dissolution as a dynamic process. Such models may allow researchers to exploit more fully temporal variation in the data.

Moreover, whilst we have focused specifically on shooting incidents, it will be important to explore how the results vary across different types of crimes. For this study, we examined only one type of social connection between neighborhoods, crime co-movement, yet neighborhoods connect with each other in many other ways, including the forging of relationships among street gangs, the lasting influence of familial ties, and the distribution of governmental resources. Thus, further experimental investigations would do well to explore the influences that a wide range of factors may have on the dynamics of shooting incidents in urban settings.

Conceiving of violence dynamics from a network perspective has implications that extend beyond researchers' efforts to understand trends in violence across a city. At a policy level, the connectedness of neighborhoods indicates that crime-prevention strategies and policies may lose some of their effectiveness if neighborhoods are treated in isolation from one another. That is, a focus on the violence levels in one neighborhood may be insufficient to reduce its rates of violence if connections between neighborhoods are playing a major role in perpetuating the violence. Policy that focuses as much on neighborhood networks as on individual neighborhoods may reveal important factors that would otherwise remain hidden and that can help reduce crime rates citywide (Graif et al. 2021).

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