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Neighborhood Isolation in Chicago: Violent Crime Effects on Structural Isolation and Homophily in Inter-Neighborhood Commuting Networks, 2002-2013

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Abstract

Urban sociologists and criminologists have long been interested in the link between neighborhood isolation and crime. Yet studies have focused predominantly on the internal dimension of social isolation (i.e., increased social disorganization and insufficient jobs and opportunities). This study highlights the need to assess the external dimension of neighborhood isolation, the disconnectedness from other neighborhoods in the city. Analyses of Chicago's neighborhood commuting network over twelve years (2002-2013) showed that violence predicted network isolation. Moreover, pairwise similarity in neighborhood violence predicted commuting ties, supporting homophily expectations. Violence homophily affected tie formation most, while neighborhood violence was important in dissolving ties.

Keywords

Neighborhood networks; Commuting; Violence; Social isolation; Homophily; Tergm

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A fundamental concern about impoverished urban neighborhoods, highlighted most notably in Wilson's classic works, *The Truly Disadvantaged* (1987) and *When Work Disappears* (1996), is that such neighborhoods and their residents are socially isolated. Wilson defined social isolation as the "lack of contact or of sustained interaction with individuals and institutions that represent mainstream society" (1987:60). Isolation limits neighborhood residents' access to jobs, role models, political influence, resources, and other important organizations and institutions. Notably, neighborhood isolation is linked to weakened formal and informal social controls and increased crime and violence (Wilson 1996). From the early Chicago School until modern times, theorists of crime, social disorganization, and urban distress have focused intensively on communities' *internal* dimension of social isolation reflected by the inadequacy of institutional infrastructure and dysfunctional social

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interactions and collective socialization within the community (Shaw and McKay 1942; Sampson, Raudenbush, and Earls 1997) — ideas sometimes summarized as neighborhood social capital (Neal 2015; Sampson and Graif 2009b).

Implicit in Wilson's classic definition is the equally important, yet much less studied, *external* dimension of social isolation — the extent to which a community lacks *extra-local ties* to outside jobs, resources, and other organizations and institutions, located in neighborhoods in the rest of the city. Even the most dysfunctional and violent communities may be connected in one way or another to other communities. Regular citizens may routinely cross neighborhood boundaries as they go to work and participate in daily activities (Krivo et al. 2013). Co-offending networks may cross large distances between neighborhoods within a city (Schaefer 2012). Yet, with few exceptions (Velez et al. 2012; Sampson and Graif 2009a; Sampson 2012), little systematic attention has been paid to external isolation. Almost three decades after Wilson's insight, we still know very little about what shapes' community disconnectedness from the world and what role violence plays in it. The current study bridges this gap by examining how violence affects neighborhoods' external connectedness to the city-wide commuting network.

Extra-local connections can be highly significant in shaping neighborhood outcomes. Work on public social control underscores how a community's ties to influential external actors can shape the allocation of public services and funds above the neighborhood level (Hunter 1985) -- with important consequences for itself as well as other neighborhoods. For example, an increase in policing resources in one community may cause crime to spill over into nearby areas (Bursik and Grasmick 1993). Neighborhoods that are isolated from the city are thus less able to influence supra-neighborhood decisions (Bursik 1989; Bursik and Grasmick 1993). In the same vein, the political economy literature highlights how "as cities grow and government bureaucrats seek sites for devalued projects (for example sewage plants, jails, halfway houses) they look first […] to poor people's neighborhoods" (1Logan and Molotch 2007 [987]: 113). In low-income neighborhoods, residents do not have the ability to collectively organize in their own interests due to lack of social capital and weak ties to influential people in the city (Logan and Molotch 2007[1987]). In contrast, residents of more advantaged and better connected neighborhoods may use their status and influence to shape of the city in their favor through such decisions as zoning regulations and the placement of transportation routes.

Investigating the patterns and determinants of neighborhoods' external isolation and connectivity holds strong promise for advancing our understanding of urban processes of neighborhood change and for changing the future trajectory of violent communities (Hunter 1985; Sampson 2012). For many distressed neighborhoods, extra-local ties may constitute a way to overcome internal deficiencies and break out of the downward spiral of social and economic distress. To the extent that large groups of people travel to other neighborhoods for work or other activities, they may forge invisible lifelines across space, through which critical information and resources may travel. Understanding how violence shapes neighborhood isolation from larger citywide networks may uncover unique avenues for distressed neighborhoods to gain economic and political leverage to alleviate existing distress (Graif et al. 2014; Velez et al. 2012).

External isolation may weaken residents' bridging *social capital*, otherwise forged through diverse ties at work and conversations with residents of other communities. Inadequate access to extra-local economic opportunities likely also means insufficient access to a broad range of services, such as job training programs, health services, or recreation centers. As individuals and communities miss out on a diverse pool of social and institutional contacts, their social capital weakens (Neal & Neal 2014; Neal 2015; Stivala 2016), which in turn will weaken further referrals for jobs and other services. If we do not understand how violence restricts neighborhood embeddedness in the wider social infrastructure of the city, we risk missing the full picture on how the residents of violent communities (the majority of whom are not involved in violence) may draw from extra-local resources to overcome local deficiencies.

Violence may be a significant driver of neighborhood isolation. As a result of violence, communities lose socially mobile residents and successful organizations (Stark 1987; Morenoff and Sampson 1997), which take their tax payments and positive role-models elsewhere. Similarly, violence may weaken a community's external connectivity to areas and organizations in the city. The lack of resource inflows into a community because of overall isolation from the citywide resource network or because of differential exclusion from ties to influential areas will affect residents (e.g., reducing funding for street lights) in addition to the high risk of victimization and of children becoming entangled in gangs and illegal drug markets.

The current study analyzes patterns of inter-neighborhood connectivity using information on the location of employers in Chicago matched to the residential location of employees between 2002 and 2013. We investigate the extent to which violence increases neighborhoods' disconnectedness from the city-wide network of resources and opportunities or contributes to differential disconnection—mostly from other safer, more advantaged neighborhoods but not from other violent neighborhoods. To the extent that violence affects neighborhoods' external network embeddedness, the findings have the potential to advance our understanding of the processes that produce and re-produce social isolation.

Neighborhood violence and network isolation

Violence may affect a neighborhood's isolation from the citywide commuting network in multiple ways. Directly, violence increases residents' concerns about the safety of public transportation (e.g., gang presence or illegal drug activity on one's way to the bus stop) (Harding 2010) and about the reliability of private transportation (e.g., stolen or disassembled cars). Increased victimization risk discourages residents' use of transportation to search for jobs and affects their informal interactions with friends and neighbors for job referrals. Wilson highlights reports from residents of dangerous neighborhoods in Chicago's South Side who feel trapped (1996: 60): "I stay home a lot. Streets are dangerous. Killings are terrible. Drugs make people crazy. […] I'm afraid to go outside. I know people who go to work and leave the music on all day and night." All else equal, these patterns suggest that residents from violent areas may be less likely to commute over larger distances than residents from safer areas. In the aggregate, this contributes to violent neighborhoods becoming more isolated from the commuting network.

Violence inevitably affects a neighborhood's reputation, as repeated media reports of crime in the area remain vivid in the public memory. Stigma associated with neighborhood location has been reflected in numerous historical efforts at "redlining," the practice of classifying certain neighborhoods as risky and denying, or selectively raising the prices of, mortgages, business loans, insurance, and other services for residents of such areas (Massey and Denton 1993; Pager and Shepherd 2008). A randomized study (Besbris et al. 2015) across multiple cities has shown that neighborhood stigma (measured as disadvantage and large shares of minority residents -- indices often related to violence as well) discourages economic transactions (rates of response to sales posts of used mobile phones on an active online market). Similar patterns may work even more forcefully in shaping employers' interest in job candidates.

Employers are known to discriminate against job seekers with criminal records (Pager 2003; Pager et al. 2009). If violent communities have a disproportionate number of individuals with criminal records, this would contribute in the aggregate (as a compositional effect) to fewer ties to all other communities, increasing neighborhoods' structural isolation. Communities with higher rates of violence likely also contain more residents with criminal records for several reasons. First, a large proportion of violence is committed within offenders' residential neighborhood (e.g., Tita and Griffiths 2005). Second, housing and employment discrimination based on criminal record restricts ex-offenders to few residential options, leading many former prisoners to return to their previous neighborhoods of residence or to neighborhoods that are similarly disadvantaged and violent (Kirk 2009, LaVigne et al. 2003). Moreover, high concentrations of ex-inmates increase recidivism (Kirk 2015) and violence (Clear et al. 2003).

Beyond a compositional effect, employers may discriminate based on neighborhood location. Though the effect of neighborhood violence has not been much examined, one study that comes close is Bertrand and Mullainathan's (2004). They used a randomized design to study labor market discrimination in Boston and Chicago by sending fictitious resumes to help-wanted ads in the Boston Globe and Chicago Tribune between 2001 and 2002. They found that living in a neighborhood that was less wealthy, less educated, or less white decreased callback rates. Since these neighborhood attributes tend to be correlated with violence, the findings can be instructive and indicative that neighborhood violence may also decrease extra-local employment.

Employers may worry that residents of violent neighborhoods are more likely to be criminal or to lack a good work ethic; that long commuting distances may render workers tardy, absent, or tired; or that wealthy white local costumers may prefer not to interact with disadvantaged minority workers from violent inner city neighborhoods (Gobillon et al. 2007). Wilson (1996) presents several reports, from employers and job seekers alike, which illustrate these points. For instance, a young unemployed black man noted, "If you're from a nice neighborhood, I believe it's easier for you to get a job and stuff. I have been on jobs and such and gotten looks from folks and such, *'I wonder if he is the type who do those things that happen in that neighborhood'"* (Wilson 1996:138, italics added).

Violence in a neighborhood likely weakens social interactions among neighbors, which will in turn affect the frequency and quality of job referrals that would otherwise occur locally. Hallerstein et al. (2014) showed evidence suggesting that social connections between neighbors affect how residents find out about jobs and about the employers who eventually hire them, lowering turnover. The hiring effect was especially strong for less skilled workers (Hallerstein et al. 2011). This suggests that if violence reduces social connections between neighbors, job referrals will be reduced. Furthermore, if in violent neighborhoods fewer people work legally for pay or work extra-locally, then even fewer new hires would be matched to extra-local establishments, further increasing neighborhood isolation from the citywide commuting network.

Indeed, a major internal dimension of neighborhood social isolation is that few residents are employed (internally or externally) and that local job opportunities become rare to non-existent. In the wake of major riots in cities like Chicago and Los Angeles, Kain (1968) proposed a *spatial mismatch* thesis to highlight that the poor employment outcomes of disadvantaged population groups were related to the increasing distance between where they lived in segregated inner-city neighborhoods and where the jobs were located. In Rust Belt cities especially, industrial restructuring led to jobs becoming increasingly decentralized by moving away from inner city neighborhoods (Gobillon et al. 2007), which contributed to fewer opportunities for entry level jobs within accessible distance. Several mechanisms have been proposed as to why the distance between home and work neighborhoods is so problematic. First, distance to jobs decreases the chances for individuals to learn about job opportunities (Selod and Zenou 2006). Second, distance to jobs increases the cost of the job search (Stoll 2005). Third, wages are effectively lowered by the costs of long commuting, child care, and deficient transportation (Ong and Miller 2005). When people cannot access entry level jobs nor do they interact with employed role models in the neighborhood, they lose opportunities to build the experience and social skills needed to expand their search more widely and to be successful in securing jobs outside the neighborhood (Wilson 1987; 1996).

Spatial mismatch focuses on existing local jobs moving out of and farther away from disadvantaged neighborhoods -- further increasing local disadvantage. When residents have to work in communities farther from their home neighborhood, longer commuting times translate into longer times away from their home, which means less supervision of their children and fewer eyes on the street, to the detriment of informal control in their own neighborhood. In contrast, the public control and extra-local ties argument focuses on the how a neighborhood’s external ties add to, or compensate for the absence of, internal resources. To the extent that social forces like violence lead to a disappearance of local jobs as well as a weakening of ties to extra-local jobs, both perspectives converge in indicating a further deepening of neighborhood distress.

Violence may affect not only the formation of commuting ties (i.e., new hiring) between neighborhoods but also tie dissolution (i.e., employment termination). Fear of crime may contribute to the dissolution of ties to the outside world, as customers stop traveling to shops and restaurants in violent neighborhoods for fear of victimization, and any existing businesses go bankrupt or leave (Greenbaum and Tita 2004). Violence and associated markers of social disorder (e.g., “broken windows”) decrease housing values, attracting mostly poor and transitional population groups to the neighborhood. Residential instability, in turn, weakens the social fabric of neighborly interactions and decreases the chances of job referrals. As a result, the connectedness of violent neighborhoods to the outside world weakens. In the other direction, employment over long distances may be terminated when workers in violent neighborhoods cannot safely access transportation or when they or family members fall victim to violence, which leads to loss of work days due to injury, disability, or time spent as a witness in court.

Overall, whether directly or indirectly, through tie formation or dissolution processes, prior work suggests expectations that violence will lower the connectivity of a neighborhood’s residents to extra-local jobs, increasing the neighborhood’s isolation from the commuting network of the city. In other words, we expect the following:

> Network isolation hypothesis -- The higher the violence of a neighborhood, the lower the probability for it to have commuting ties to other neighborhoods in the city, controlling for other neighborhood factors that also contribute to violence and disconnectedness.

Homophily in inter-neighborhood commuting ties

It is important to note that resources and institutions are not always absent from impoverished neighborhoods (e.g., childcare programs like Head Start) and when present, they do connect their clients to resources and institutions across the city (Small and McDermott 2006; Murphy and Wallace 2010; Tran et al. 2013). Even then, important questions remain about the quality of such connections. Are impoverished and violent neighborhoods connected to areas of better quality or to similarly distressed areas?

Researchers have long noted the strong similarity among people, organizations, or communities connected through various forms of relations, including friendships, work connections, discussions (Ibarra 1995; Marsden 1988; Neal and Neal 2014) and even in patterns of crime victimization (South and Felson 1990; South and Messner 1986; Sampson 1984). Shared race, ethnicity, religion, education, and social class status have all been shown to increase the likelihood of inter-personal and inter-organizational ties (McPherson et al. 2001). For instance, Galaskiewicz and Shatin (1981) indicate that connections between community organizations during challenging times are most likely activated based on similar background.

While connections between neighborhoods have rarely been studied, some important indications of homophily in inter-neighborhood ties have been emerging when links were defined based on community leadership (Sampson 2012), residential mobility flows (Sampson and Sharkey 2008), co-offending partnerships (Schaefer 2012), and inter-gang conflicts (Papachristos et al. 2013). These types of ties may be related to residents’ work location, suggesting that commuting connections may also be affected by inter-neighborhood similarities. Community psychology studies have found that humans’ tendency toward homophily and proximity in forming and maintaining ties contributes to an inverse relationship between community cohesion and diversity. Still, under certain conditions heterogeneous ties may be sustainable as well. For instance, social capital dimensions of bridging and bonding were both found possible in segregated local neighborhoods within diverse larger communities (Neal 2015). Furthermore, segregation based on characteristics like race may be overcome when similarity exists on other, mutable characteristics (Stivala 2016).

A violent neighborhood's reputation may prevent ties from forming in general, yet the degree to which this works may differ based on the violence level in the extra-local neighborhoods where jobs are located. Employers located in non-violent neighborhoods may be less likely to hire job seekers from violent neighborhoods for the same reasons that contribute to neighborhood isolation, noted above. However, employers located in other violent neighborhoods may be less likely to discriminate on this basis, perhaps due to limited hiring options or a desire to help people from disadvantaged backgrounds. Additionally, employers in violent neighborhoods may be less likely to stigmatize applicants from similar neighborhoods to their own. Combined, these patterns may contribute to homophily in inter-neighborhood tie formation on the basis of residential violence levels.

Once the ties are formed, however, the patterns may be less clear-cut in shaping tie dissolution or persistence. Employers in low-violence neighborhoods may still discriminate based on worker's neighborhood location if they learn about it after the hiring stage. Additionally, workers' commuting to high violence neighborhoods may also be disrupted by safety threats in the work neighborhood. Together these patterns may counterbalance each other, contributing to expectations of a non-significant effect of violence similarity on tie dissolution.

While the role of similarity in neighborhood violence in predicting the structure of commuting networks in urban environments has not been yet investigated systematically, evidence exists that similarity in other characteristics related to violence (e.g., racial and socioeconomic status) has a positive effect on job referrals and hiring. With respect to race, Bertrand and Mullainathan's (2004) randomized study, which, as mentioned earlier, sent fictitious resumes in response to job ads, found a slightly smaller racial gap in callback rates when employers were located in more African American neighborhoods. With respect to socioeconomic status, Schmutte's (2015) study shows that workers who live in neighborhoods with networks of higher paid individuals are more likely to move to jobs with higher wage premiums. If better paid employees tend to live in better quality (presumably safer) neighborhoods, and better paid jobs tend to be located in similarly better off neighborhoods, then this finding also suggests a potential homophilic effect in connections between communities based on neighborhood quality and safety.

The similarity between people's residential neighborhoods and the neighborhoods where they work, and more generally engage in routine activities, has been highlighted in an important recent study by Krivo et al. (2013) in Los Angeles. The study found that individuals living in disadvantaged neighborhoods conducted routine activities in other areas similar in disadvantage. Those who lived in more advantaged neighborhoods similarly limited their activities to advantaged areas, which ensured that they formed and maintained contact with similar individuals and institutions (Dwyer 2007; Massey and Fischer 2003).

While the study does not conceptualize neighborhood homophily in network terms, it supports expectations of homophilic ties based on neighborhood features. Overall, the evidence suggests the following:

> Homophily hypothesis -- Pairwise similarity in neighborhood violence increases the likelihood of a commuting tie between any two neighborhoods, net of other neighborhood factors and similarities.

Data, Measures, and Methods

The measures in the current study are based on data from the Decennial Census, police records, and the Longitudinal Household Employer Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) (Abowd et al. 2005). The LEHD is a U.S. Census Bureau program that matches Unemployment Insurance earning records with other administrative records from state and local authorities to additional census and survey data on the firms, worker, and household statistics. The unemployment insurance data reported by the states covers roughly 95% of salary and wage jobs (Graham et al. 2014: 3). Excluded are data on federal employment (about 2% of the workforce), missing before 2010. Beyond the scope of the unemployment insurance forms are data on some nonprofit and religious institution employees, the self-employed, and informal workers (Graham et al. 2014). One aim of the LEHD is to create commuting flow statistics by matching employers and employees with respect to the location of establishments and residences, respectively. We use these data to generate an inter-neighborhood commuting network among all 77 community areas (CAs) in Chicago every year for a period of twelve years, between 2002 and 2013. CAs are geographic areas of about 38,000 residents on average. They have advantages over other neighborhood definitions because of their recognizable names and histories and relatively stable boundaries over time[1].

Chicago presents a valuable case study as it is the third largest city in the U.S., after New York City and Los Angeles, at about 2.896 million residents in 2000. Like many other cities, Chicago has undergone rapid industry changes. In the 1970s, the largest share of residents was employed in manufacturing, while by 2000 the largest share was employed in the service sector (though manufacturing still has a relatively large presence) (Weigensberg et al. 2011). The crime measures we use are based on reported incidents extracted from the Chicago Police Department's Citizen Law Enforcement Analysis and Reporting system and released under privacy protection through the City of Chicago's Data Portal. Data on violent crime incidents (except murders, which are recorded as one incident per each victim) were aggregated to the CA level on a yearly basis between 2001 and 2012.

The socio-demographic data are based on responses to questions asked in the U.S. Census Bureau's 2000 Decennial Census of Population and Housing. Data were first extracted at the

[1]An alternative way to redefine the nodes is based on census tracts. Because census tracts are smaller geographic areas than communities, this would mean that residents going to work in other non-proximate tracts within the same community area would be perceived as forming external ties. Such ties may be very different in character and benefits from ties to other communities. While comparing the ties between different tracts and different community areas is beyond the scope of the current study, this is a valuable research direction for the future.

census tract level through American Fact Finder and the Neighborhood Change Database (Geolytics 2003) and then geocoded and aggregated to the CA level.

Measures

The *dependent variable* is defined as a commuting relation from the home community to the work community. While ties based only on commuting do not represent all possible ties between neighborhoods, they are likely related to a broader range of interpersonal interactions and resource exchanges across space. To compute the commuting relation we used LEHD's LODES database to calculate the number of residents from a home community that commute to a work community. Then, we normalized this value by the 2000 population level of the home community. This generated a directed commuting relation network characterized by a 77 by 77 valued matrix. Finally, we binarized the matrix; if the cell's value was higher than 0.5% the cell value was set to 1 and to 0 otherwise. Thus, two communities are tied if more than 0.5% of the home community's residents commute to the work community.

Main independent variables

We calculated neighborhood violent crime rate based on the number of violent incidents located in the neighborhood during each year between 2001 and 2012, divided by the number of neighborhood residents, as assessed by the 2000 decennial census. The types of violent incidents included were homicide, assault, battery, sexual assault, domestic violence, and robbery. We used violent crime as a predictor in two different ways. First, we used the violence rates in the "home" (or sending) neighborhood and in the "work" (or receiving) neighborhood to predict network isolation. Second, we used the absolute difference between the work and home community violence to predict homophily. We used a continuous measure of community violence and lagged it by one year to precede the year when the dependent variable is calculated.

It is important to consider the reliability of violent crime data. Our crime data is made up of crimes known to the Chicago Police Department. The accuracy of this measure is therefore influenced by the reporting of crime to the police. Crimes that occur but are not reported to the police are not included in our data, as is the case with many criminological studies. Homicide is the least likely crime to go unreported to the police both because of its severity and because of the presence of a body. Indeed, the homicide data kept by the FBI closely tracks that kept by the CDC in the National Vital Statistics System Fatal Injury Reports, which are collected through death certificates rather than reports to the police (Regoeczi et al. 2014). Data on other crimes are influenced by those factors that influence the reporting of crime by victims and witnesses. Prior research has found that reporting varies by factors like crime type, race, and neighborhood socioeconomic status. For instance, simple assaults and sexual assaults are less reliably reported than robbery and aggravated assault (Baumer 2002; Baumer and Lauritsen 2010. Additionally, simple assaults are less likely reported in very advantaged and very disadvantaged neighborhoods (Baumer 2002).To address concerns about potential measurement problems with reported crime data, we conducted additional analyses using measures of violent crime that only include homicide, robbery, and aggravated assault.

Control variables

Spatial proximity—McPherson et al. (2001:429) named space as "the most basic source of homophily," drawing on the principle of least effort -- that it takes more effort to connect over larger distances. While new communication technologies have lowered the cost of forming and maintaining ties over long distances (Wellman 1996), geographic space remains powerful in influencing the presence and strength of ties (Hipp and Perrin 2009; Schaefer 2012). In our analysis, we define spatial proximity as contiguity. Two communities were considered contiguous if their boundaries touched. Spatial proximity was coded as an un-directed 77 by 77 network. The cell in the matrix is 1 if the two communities were contiguous and 0 otherwise.

Public transportation network—Given that public transportation shape the movement of residents and crime across the city (Felson and Boivin 2015), we also control for shared public transportation routes. Public transportations information on Chicago Transit Authority (CTA) bus stops, rapid transit system stations (elevated "L"), and commuter rail (Metra) stations were obtained as point data from the City of Chicago's data portal. We processed and geocoded the stations' geographic coordinates to identify their CA location. We then constructed a CA-by-CA matrix with cells equal to the number of all shared CTA bus routes, rapid transit lines, and Metra rail commuter lines. The minimum number of shared lines was 0, median 2, maximum 28. The number (and percentage) of ties with at least one shared route was 1,010 (35%); with more than 2 routes was 611 (21%). On average, CAs had shared such routes with 25.23 other communities.

Residential stability and racial and ethnic diversity indexes are composite indices calculated based on data from the 2000 Decennial Census, following prior work (Sampson and Graif 2009a; 2009b). *Residential stability* is measured as the percentage of residents 5 years old and older who resided in the same house 5 years earlier and the percentage of owner-occupied homes. In calculating the composite index score, each item was factor weighted based on results from a principal component analysis. Residential instability may increase neighborhood isolation by decreasing cohesiveness among neighbors and thus weakening job referral networks. Residential instability is also an important correlate of violence and important in the social disorganization tradition (Sampson et al. 1997). Boggess and Hipp (2010) showed that violent crime increased residential instability in a neighborhood. Additionally, experiencing victimization increases residential mobility (Xie and McDowall 2008). Controlling for residential stability will indicate if violence effects exist beyond those mediated by instability.

Racial and ethnic diversity is measured as a Herfindahl concentration index (Blau 1977; Sampson and Graif 2009a; 2009b) equal to one minus the sum of squares of the proportions of the neighborhood population made up by a racial or ethnic group: non-Hispanic whites, non-Hispanic Blacks, Hispanics, Asians, Native Americans, and Others. Higher values of the index indicate more diversity. Diversity has been shown to impact social ties. Areas with greater diversity within shorter geographic distances contribute to discussion networks of higher heterogeneity as well (Marsden 1987). Ties among actors of different characteristics are also more likely to dissolve (Hallinan & Williams 1989) when challenges emerge (Hurlbert et al. 2000). Diversity has been shown to affect violence (Graif and Sampson 2009). Controlling for diversity will indicate whether violence effects exist beyond those mediated by diversity.

Understanding the role of violence independent of other neighborhood characteristics, including racial composition is challenging, particularly in a city like Chicago, where, because of historic racial segregation patterns, racial composition is strongly correlated to disadvantage and violence. For instance, violent crime across CAs in 2012 is correlated with the percent black (r=.82), Hispanic (r=-.41), and white (r=-.70). Including information about the racial and ethnic composition using multiple strongly correlated measures leads to major collinearity concerns. To avoid multicollinearity, the main models include these measures as part of a single composite index of racial and ethnic diversity. This strategy also accomplishes an important theoretical goal, it measures more accurately than the separate racial composition variables the concept of population heterogeneity, central to theories of social disorganization starting with Shaw and McKay (1942). Population heterogeneity's role in crime is predicated on the increased tensions and misunderstandings when different population groups reside close to one another. This measure is also strongly correlated with percent black (r= -.74) and Hispanic (r=.71). Since percent black, white, Hispanic, Asian, and other are included in creating this composite scale, and since racial composition is a control rather than a primary predictor, the composite index seems to be a reasonable measure to use. Because of its advantages, this measure is a common predictor in analyses of crime and neighborhood change Hipp 2007; Graif and Sampson 2009). Furthermore, we also conducted sensitivity analyses using separate racial composition items as controls, as discussed in more detail below.

Density of local jobs was measured, based on LEHD data, as the number of jobs located in the community occupied by either local workers or workers who reside in other communities divided by the population of the community. If a community has more jobs located internally, increasing the local tax base and extra-local customers visiting the community, it seems reasonable to expect that there are also more internal socioeconomic opportunities and resources (e.g., funding for schools, police, and various local programs). As local resources tend to inversely correlate with violence, controlling for such resources will enable us to assess the violence effects on connectivity independent of potential socioeconomic effects Socioeconomic disadvantage is strongly correlated with percent black (r=.84) and violence (r=.80). Because of these strong associations, assessing the role of violence on network isolation independent of disadvantage is a challenge. Since our interest is in the role of violence on commuting to jobs in other areas, from a conceptual standpoint, a more important control is a measure of neighborhood socioeconomic status based on the local presence or absence of jobs. If local jobs do not exist, it seems reasonable to predict that commuting ties to the outside world will be more likely to form. If local jobs do exist, they can increase the access to resources and opportunities for residents. This suggests that it could be a reasonable indicator of neighborhood socioeconomic status. Still, we also conducted sensitivity analyses with disadvantage as control, as discussed in more detail in the supplementary analyses section below.

ERGM/p* and TERGM

Standard regression methods assume that observations are independent. However, the relations between communities are interdependent -- violating the independence assumption. To address this challenge, we use Exponential Random Graph Models or p* models (ERGMs/p*) (Frank and Strauss 1986; Robins and Pattison 2005; Robins et al. 2007; Wasserman and Pattison 1996). A key feature of ERGM/ p* is the ability to control for purely structural effects (also called endogenous effects). For example, commuters might decide to go to work in a specific community based on the high number of other commuters that work in that community. Specifically, in our study we control for the following endogenous effects: edges, reciprocity, and the geometrically weighted in-degree distribution (Hunter 2007). The number of edges refers to the level of commuting in the network (i.e. network density). Reciprocity refers to mutual links (i.e., there is a commuting tie between community A and community B if there is a commuting tie between community B and community A). The geometrically weighted in-degree distribution controls for popularity spread. A negative popularity spread parameter indicates that most communities have similar levels of popularity (i.e., the network is not centralized on in-degree). Similar to logistic regression, positive and significant coefficients in ERGM/p* models indicate that the corresponding structures are more likely to occur than by random chance.

We investigate inter-neighborhood commuting networks among the 77 CAs in Chicago, as they remain stable or change from one year to another, for a period of twelve years, between 2002 and 2013. The ERGM models are cross-sectional, using data separately for each year. In the interest of space, Table 2 presents models for a selection of only four years. Given the longitudinal characteristic of our dataset, we next used a recently developed extension of ERGMs called Temporal Exponential Random Graph Models (TERGM) (Hanneke and Zing 2007, Hanneke, Fu, and Zing 2010, Robins and Pattison, 2001) to analyze patterns of tie formation and dissolution in our data using data for all twelve years. The TERGM allows for modeling dynamic networks (i.e., networks that evolve over time) and provides two different sets of parameters: one set of parameters that estimates formation of new ties in the network and another that estimates dissolution (or persistence) of current ties. These two sets of parameters are generated by two equations: the formation and the dissolution of ties. Each of these two equations is an ERGM model. The formation model estimates the probability of a tie to form in the network conditional on the tie not existing at the prior step, while the dissolution model is conditional on the tie existing at the prior step. The coefficients in the dissolution model reflect the odds of an existing tie to persist. The probability of dissolution can be calculated from this as 1 – persistence. TERGM models formation and dissolution processes jointly. While the two are modeled to be dependent over time, they are conditionally independent within any given year (Krivitsky and Handcock, 2014; Handcock et al. 2015).

Inter-neighborhood commuting networks

Figures 1 and 2 graphically present the 77 community areas of Chicago and their commuting network. Both graphs of Figure 1 show the geographic distribution of communities. The leftmost map also depicts the geographic boundaries and the CA names, whereas the rightmost map shows a simplified representation of communities as nodes (circles located at the latitude and longitude coordinates of the CA centroids) connected through the 2013 commuting ties (0.5% cutoff). The size of the nodes varies proportional to the violent crime index score (i.e., more violent CAs have larger nodes). The color of the node is based on out-degree: darker nodes are more isolated (i.e. community with fewer outgoing ties). The map highlights that the highest concentrations of violence are located in southern and some of western Chicago. With few exceptions (such as the downtown area, the Loop, which is both high in violence and well connected), most of the large size (high violence) community nodes tend to be relatively more isolated than the small size (lower violence) community nodes.

Figure 2 uses Force Atlas 2 which implements a continuous force directed layout algorithm that determines the position of each node based on a principle of attraction/repulsion to neighboring nodes (Jacomy et al. 2014). The idea behind the simulations that shape the layout is that the nodes repulse and the edges attract. This graph shows that, with some exceptions, the higher violence (large size) and more isolated (darker shade) communities tend to cluster together (bottom cluster) and so do communities of lower violence and isolation levels (rightmost cluster). These patterns suggest that similarly violent communities may be connected to each other more than those that are dissimilar in violence, indicating homophily by violence.[2]

Descriptives

Table 1 reports the means, standard deviations, ranges, and correlations of the core neighborhood level measures in this study for 2002 and 2013 in order to give a sense of the temporal bounds of the values. We use 0.5% in defining the ties, which represents about 11% of all possible ties in 2002 and 9% in 2013. First, Table 1 presents information on neighborhood violence. The mean violent crime rate decreased over the course of the years, following the general pattern of decreasing crime in the United States during the same time. In 2001 the average violent crime rate across the 77 CAs was 0.05 while in 2012 the average violent crime rate was 0.03. Between the most and least violent areas in the data, there is a large range in violent crime rate. The least violent area had a rate of only 0.01 in 2001 and of 0 in 2012 compared to the highest rates being 0.16 and 0.1 in those years, respectively.

Next, Table 1 presents descriptive information about the demographic characteristics of the CAs in our sample. CA disadvantage is on average -0.04, ranging from -1.24 to 2.38. The mean of residential stability is -0.01, ranging from -2.11 to 1.73. Diversity averaged 0.12, ranging from -1.54 to 2.4. Table 1 additionally presents descriptive information on the

[2]The geographic maps and the community centroid coordinates in Figure 1 were created using ArcGIS 10.2 while network visualizations in Figures 1 and 2 were done using Gephi 0.9.1 (Bastian, Heymann, and Jacomy 2009).

residential locations of workers. The local job density averaged 0.35 in 2002 and 0.36 in 2013, ranging from 0.02 to 12.18 and 13.85, respectively.

Finally, Table 1 presents information on neighborhoods' connections to other neighborhoods in the city. In 2002, the neighborhoods had on average connections to 8.3 other neighborhoods. The neighborhood with the fewest outgoing connections had only two while the neighborhood with the most was connected to 14 other neighborhoods. The most amount of incoming ties was 76 (representing CAs that received commuters from every other area in the city, such as the Loop, Near North Side, Near West Side, as well as South Chicago). The least amount of incoming connections that a neighborhood had was 0 (representing an in-degree isolate). Across all of the years in the data, 34 CAs on average were isolated based on their in-degree. The year with the fewest isolates, 2002, had 25 while the year with the most, 2010, had 41. Overall, across the twelve years in the sample, the number of CAs that were isolates increased. In 2013, the average in-degree and out-degree decreased somewhat from 2002, although the minimum and maximum remained similar.

Multivariate ERGM/P* estimates: Static and dynamic network models

Table 2 presents the results of the ERGM/p* technique predicting the likelihood of a commuting relation between two communities. Model 1 includes the endogenous effects (i.e., network structure), attribute effects (i.e., sender and receiver effects), and spatial proximity. Model 2 adds the difference in violent crime rate between the "home" and "work" community. Finally, Model 3 controls for the difference in residential stability, diversity and density of local jobs between the "home" and "work" community (i.e., dyadic shared attributes). We ran the analysis for each year from 2002 to 2013. However due to space constraints, we present only the 2002, 2005, 2009, and 2013 results.

The focus of our study was to explain the effects of neighborhood violence on isolation from the commuting network. The network isolation hypothesis predicted that the more violence in a sending (or receiving) neighborhood, the lower the likelihood of a commuting tie. The results indicate that, net of social and demographic characteristics of home and work communities, the higher the violent crime rate of the "home" community, the lower the likelihood of people from that community to commute to work outside (i.e., negative sender effect of violent crime rate). Similarly, the results indicate that the higher the violent crime rate of the "work" community, the lower the likelihood of outside people to commute to work in this community (i.e., negative receiver effect of violent crime rate). These findings are consistent with the network isolation hypothesis.

The homophily hypothesis predicted that the greater the similarity in violence levels between two neighborhoods the higher the likelihood of a connection. The results for model estimations in 2002 indicate that, indeed, the higher the difference in violent crime rate between two CAs, the lower the likelihood of a commuting relation. In other words, neighborhoods with higher rates of violent crime are more likely to be connected to other neighborhoods with high violent crime and much less likely to be connected to neighborhoods with low rates. This positive association of similarity with tie formation is an indicator that homophily is an important force in our network. The results hold even when controlling for dissimilarity in residential stability, racial and ethnic diversity, and density of local jobs (Model 3). These findings are consistent with the homophily hypothesis. The homophily pattern is largely consistent across the years as well, with some loss in precision from 2010 on. In 2013, for instance, the coefficient of violence (dis)similarity was marginally significant in two-tail tests.

As mentioned earlier, we control for endogenous effects, characteristics of the commuting network structure, spatial proximity, and dyadic shared attributes (i.e., similarity of commuting attributes). We next describe these results. Overall, several network structure characteristics are significant predictors of ties across all the ERGM models. The coefficient for edges is consistently significant and negative. This indicates that commuters do not "go to work" to a neighborhood randomly because forming commuting relations is costly. Similarly, the geometrical weighted in-degree (popularity spread) also has a consistently significant negative effect on the likelihood of ties. This suggests the commuters do not choose a specific community to work only because that community has a high number of commuters. Reciprocity is not statistically significant. This indicates that there is not a particular tendency in the network for reciprocity in the relationships between sending and receiving neighborhoods. In other words, a directed commuting tie from neighborhood A to neighborhood B does not increase or decrease the likelihood of a directed tie from neighborhood B to neighborhood A.

Next, we turn to the demographic and socioeconomic nodal characteristics in the ERGM models. For the residential neighborhood, residential stability and diversity both tend to increase the likelihood of a tie. For the work neighborhoods, local job density is positively associated with ties. Next, spatial proximity and transportation links are consistently positive and significant. This indicates that ties are more common between neighborhoods with shared boundaries or shared transportation routes. Finally, the ERGM models control for a set of dyadic similarities. The results indicate that dissimilarity between neighborhoods in their levels of residential stability, racial and ethnic diversity, and density of local jobs are in some years, negatively associated with a tie. In other words, as differences between neighborhoods on these features increase, they are less likely during some years to be connected to each other.

Table 3 presents the results of the TERGM estimations. As mentioned earlier, these help us draw from longitudinal information on network changes over time to estimate separate models of tie formation and dissolution. We estimated the TERGM model using a parallel parameter specification as in ERGM Model 3 (see Table 2). Each TERGM model is estimated based on all twelve waves of data (from 2002 to 2013). The first set of models in Table 3 presents estimates for the effects of the covariates on the log odds of a tie forming. The second set of models in Table 3 presents estimates for effects of covariates on the log odds of an existing tie to *persist*.

First, the TERGM results for tie formation show a nonsignificant coefficient of home neighborhood violence and a positive coefficient of work neighborhood violence. The network isolation hypothesis is thus not supported at the formation stage. Nonetheless, pairwise similarity in violence has a strong influence over tie formation, in support of the homophily hypothesis. The significant, negative coefficients for the absolute difference terms indicate that as neighborhoods are increasingly different in their levels of violence, residential stability, and diversity, they are less likely to form a connection. Conversely, this indicates that as neighborhoods are more similar in these characteristics, they are more likely to become tied. This result is robust to controlling for network structure and neighborhood demographics.

The structural measures of edges, reciprocity, and the geometrically weighted in-degree follow the same pattern shown in the ERGM models. Work neighborhoods that are more diverse and residentially stable have decreased odds of tie formation while for residential neighborhoods, those characteristics increase the odds of tie formation. Finally, local job presence has a positive effect on the odds of tie formation for both work and residential neighborhoods.

The second set of models of the TERGM estimations indicates the logged odds of existing ties to persist. These are considered "dissolution" models because dissolution is 1 - persistence (Handcock et al. 2015). In this model, we find evidence of isolation. For both work and residential neighborhoods, increasing violent crime rates are associated with decreased odds that existing ties will be maintained. These results indicate support for the isolation hypothesis at the dissolution/persistence stage. Other characteristics of the residential neighborhood are not statistically associated with tie persistence. However, work neighborhoods are significantly less likely to maintain ties as their residential stability and diversity increase, while they are significantly more likely to maintain ties as local job density increases. In the dissolution model, only the difference term for diversity is statistically significant. Connected neighborhoods that have different levels of diversity are thus less likely to maintain a tie. Finally, of the structural covariates, edges (density) and popularity spread are significantly associated with tie persistence.

Each variable is measured differently from the others making direct comparison among coefficients challenging. For more comparable units, we standardized the variables such that for each year, their mean across communities equals zero and standard deviation equals one[3]. The TERGM estimates indicate that one standard deviation increase in violence in the home community is associated with -.26 log odds of a tie, (OR = .77), about a 33% decrease in the odds of an existing tie to persist. The only other home community nodal characteristic that was significantly associated with persistence was diversity (log odds = .20, OR = 1.22), which increased the odds of an existing tie to persist by about 22%. An increase in the absolute difference in violence between home and work communities of one standard deviation is associated with a significant decrease in the log odds of a new tie to form (-.23, OR = .79) -- a decrease of about 21% in the odds of a commuting tie to form to another community. In comparison, an increase of one standard deviation in pairwise differences in residential stability, local job density, or racial and ethnic diversity between communities decreases the odds of a commuting tie to form by 27%, 15%, and 13%, respectively. In other words, similarity in violence levels increases the odds of a tie to form between any two communities, an effect that is both independent of, and stronger than, the effect of similarity in diversity or in local job density.

[3]When dividing the unstandardized coefficient by the standard error, the relative patterns of effects did not change.

Finally, Table 4 presents results of TERGM models with more specific measures of violent crime: homicide, robbery, and robbery and aggravated assault. The models in Table 4 provide support for both the isolation and homophily hypotheses. The isolation hypothesis is supported by the consistent significant and negative effect of residential violence on both the formation and persistence of ties. Together these results indicate that as a neighborhood's violence increases it is less likely to develop ties to other communities and the existing ties that it has are unlikely to persist. Additionally, we find support for the homophily hypothesis in the significant negative effect of crime dissimilarity on tie formation when crime is measured by robbery and aggravated assault and robbery alone. In other words, neighborhoods are more likely to be tied if they are similar on all violence as well as on more narrow types of violence levels. For homicide the coefficient had the same direction as for the other violence types but was not significant. The weaker precision in the effect could be due simply to a meaningful difference in effect by crime type or to the fact that homicides are rarer than other crimes.

Supplementary Analyses

Different cutoffs and tie strength—In additional analyses, we eliminate the need to choose a particular threshold value in dichotomizing the ties by using a multiscale backbone extraction algorithm (Serrano et al. 2009) to redefine the commuting networks. This procedure preserves only links with weights that significantly deviate from a null model (which determines the expected distribution of link weights around a node if those weights were distributed randomly). We then re-estimated our main, fully controlled models (model 5 of Table 3). The results (described in Appendix Table A1) are consistent with our main prior findings that a) home-to-work violence homophily significantly increases the chances of forming a new tie and b) violence in a residential community isolates it from the rest of the city by dissolving existing ties. Two minor differences emerged. First, the residential community violence became significant and positive (rather than non-significant) in predicting tie formation. This effect however, turns back to non-significant when using the more specific crime measures, presumably less affected by reporting bias (models 2a-4a). Second, the previously negative coefficient of violence in the working community on tie persistence becomes non-significant when using the all violent crime index (model 1b). Still, this coefficient becomes marginal or fully significant again in models that include only the narrow violence indices. Despite the minor difference, the main results are consistent between the threshold and the backbone models.

We also conducted backbone analyses with larger and smaller alpha values to vary tie strength, 0.10 and 0.01. The analyses did not converge at alpha=.10, but did for alpha=.01 (see Appendix Table A3 model 4). The findings were consistent with the main results in indicating a violence homophily effect on tie formation. Furthermore, residential violence rate decreased tie formation and work violence increased dissolution. Residential violence positively affected persistence, indicating that, when community ties are strong, commuters are more able and motivated to keep their jobs as home area violence rises. When using the narrower crime categories (tables available at request), the results are consistent to those based on all violence, with the exception of the residential violence effect on tie persistence, which turns non-significant for robbery and aggravated assault.

To explore how results in the threshold approach change with the strength of the tie, in further analyses, we defined ties based on additional cutoffs (c), such as 0.25%, 0.30%, and 1%. We first redefined the ties more broadly, to include weaker ties, c = 0.25% This represents a neighborhood average of 94 commuters per sending tie, SD = 61 and a total of 1261 ties (about 22% of all possible ties) in 2002 and 1078 ties (18%) in 2013. TERGM models for this definition of the ties failed to converge when including all twelve years of data. We instead report results based on ten years of data (2002-2011), which did converge. The TERGM estimations presented in Appendix Table A3 are otherwise equivalent to Table 3's fully controlled models (model 5). The findings show that similarity in violence significantly predicts tie formation, consistent with the homophily hypothesis. Violence in both the sending and receiving communities significantly decreased the likelihood of an existing tie's persistence, consistent with the isolation hypothesis, while similarity in violence between sending and receiving communities contributed significantly to tie dissolution, also supporting the homophily hypothesis. Furthermore, when defining the tie for c = 0.30% (converged years, 2003-13). [4], the violence effect on homophilic tie formation emerges again, as does the isolating effect of residential violence on tie persistence.

Next, we redefined the ties more narrowly, to refer to stronger ties, c = 1%. Across all neighborhoods, on average, this refers to 376 commuters per sending tie, SD = 243 and a total of 317 ties (about 5.4% of all possible ties) in 2002 and 277 (about 5 %) in 2013. Results from TERGM estimations otherwise equivalent to the main models of Table 3 are presented in Appendix Table A3. Violence homophily was not significant after adding controls for similarity in residential stability and diversity. This indicates that the effects of similarity in violence on the stronger ties may be fully mediated by similarity in sociodemographic characteristics. The homophily effect in depressing tie formation remerged again in models focused only on robbery, indicating potential differences by crime type. The isolating effect of all violence in a sending community on tie formation or dissolution was not significant. Nonetheless, in the robbery and robbery and aggravated assault models (not shown), residential community violence exhibited a significant isolating effect at the formation stage, robust to the added controls, adding to the support for the network isolation hypothesis.

In sum, analyses indicated that the isolating effect of community violence shapes in one form or another the commuting networks based on both weaker and stronger ties. Moreover, for weaker ties, the homophilic effect of violence may affect both tie formation and dissolution, while for stronger ties the homophilic effect of violence matters more at the formation stage.

Additional controls—We conducted additional sensitivity analyses with various other control variables, such as disadvantage, detailed racial and ethnic composition indices, percent foreign born, and population density. *Disadvantage* was calculated as a composite index based on the percentages of residents below the poverty line, receiving public assistance, unemployed, and of female-headed families with children. Because of strong correlation among these items, the disadvantage scale was calculated as a function of the

[4]For c = 0 .20% (converged years, 2003-2011) the results are similar with those for c = 0.25%.

factor scores from principal component analysis of the items. *Population density*, calculated as a function of the number of residents per square feet area, may influence a neighborhood's isolation in multiple ways. For example, population density may provide larger social networks for residents to draw upon when seeking out a new job (Granovetter 1973). As a result, dense neighborhoods should have lower levels of isolation and homophily. Additionally, population density is related to neighborhood violence, as high violence rates are associated with population loss (Moreonoff and Sampson 1997).

To include separate *racial composition* characteristics as controls (instead of the composite index of racial and ethnic diversity), we used two measurement strategies. First, we included percent non-Hispanic black, and percent Hispanic in addition to disadvantage, stability and population density and the core findings follow similar patterns as with the next strategy (tables available at request). Second, we used itemized racial regime indicators to control for predominantly black, Hispanic, and white communities based on whether a racial or ethnic group represented over 60% of the population or not. We chose this over other thresholds to have a more balanced distribution of neighborhoods across categories. This yields 29 predominantly black communities, 17 white, 10 Hispanic, and 21 mixed (no group was over 60%). Models 1 and 2 also control for disadvantage instead of job density, in networks based on c=.005 and based on the backbone procedure, alpha .05, respectively. The findings indicate that the significant homophilic effect of violence on tie formation remained robust to the added controls, as did the isolation effect of residential community's violence in dissolving existing ties (Appendix Table A2). These findings are consistent with the main results (model 5b, Table 3). Some more minor differences also emerge. The coefficient of home community violence became significant in the formation model 1a based on c=.005 but turns non-significant again when redefining the tie through the backbone procedure. The coefficient for work community violence level becomes positive in predicting persistence of the working community in both models 1b and 2b. This difference from the main results suggests that a working community's violence level remains a proxy for jobs or other resources that decrease the odds of ties to dissolve. When adding neighborhoods' population density to models otherwise equivalent to those in Table A2, the estimation failed due to many highly correlated terms.

Discussion

This study investigated the role of violence in predicting neighborhood isolation and differential exclusion from the ecological network structure of commuting flows across Chicago over the course of twelve years. Results from analyses of commuting networks showed that violence is significantly associated with commuting connections to fewer communities. Cross-sectional analyses, net of controls, indicated that during most years, violence in the residential and work neighborhoods was associated with isolation, and similarity in violence contributed to connection. Results from dynamic models suggested that pairwise similarity in violence between neighborhoods increased the likelihood of a tie forming between previously unconnected communities, suggesting patterns of homophily in tie formation. The homophily is robust to controlling for nodal and dyadic covariates, including neighborhood levels of violent crime.

Conceptually, homophily is a form of neighborhood isolation. The findings suggest that, even when violent neighborhoods are not excluded fully from the city-wide commuting network, they are *differentially excluded* from resources and opportunities in safer neighborhoods throughout the city. It is instructive that homophily predicts tie formation but does not prevent dissolution. Once formed, homophilous ties are as likely to dissolve as heterophilous ties. The observed differential sorting patterns are consistent with mechanisms related to employer and worker behaviors. Employers in safer communities may be more likely to hire job seekers from similarly safe communities. Prior work has shown that employers may worry that job applicants from violent neighborhoods may be violent themselves or not have a good "work ethic" (Wilson 1996). Since employers in violent communities may not have as many options to hire job seekers from safer home areas, they may not be as likely to exclude job seekers from violent home neighborhoods. Additionally, observed homophily in tie formation based on racial and ethnic diversity, residential stability, and density of local job presence is consistent with Bertrand and Mullainahan's (2004) findings which suggest employer-employee race-based homophily in hiring and with Schmutte's (2015) findings of income-based homophily in hiring.

To the extent that the homophily patterns are related to job seekers' behavior, the results are consistent with job seekers not applying for jobs in communities that are too different from their own, perhaps because they anticipate discrimination. If they do apply, they may not know the norms to navigate the job interview successfully (e.g., follow "proper" dress code). Common strategies of survival in violent home neighborhoods (e.g., not looking people straight in the eye) may not be perceived well by employers in dissimilar neighborhoods, who may worry about misperceptions customers of the advantaged workplace neighborhood (Gobillion et al 2007).

Results also indicated that violence in a residential (sending) community contributed to a lower likelihood of an existing commuting tie to persist over time. The violence rate in a workplace community also predicts tie dissolution. Net of homophily effects, home neighborhood violence contributes to network isolation at the tie dissolution stage. This is consistent with Wilson's classic sociological insights on "social isolation" (1987, 1996) and with a long thread of scholarship on spatial mismatch (Kain 1968). Overall, the robust findings of violence effects on homophilic tie formation and isolation through dissolution suggest that constraints in *maintaining* long distance jobs may be as important as constraints in obtaining such jobs. From the employers' standpoint, if discrimination exists based on neighborhood violence reputation, it may operate even *after* the hiring stage, when the employer learns more about the new employee. From the standpoint of workers living amidst violence, employment ties to extra-local jobs may dissolve when commuters' child care options become too expensive or unreliable, or as transportation options become unreliable, or unsafe (Ong and Miller 2005).

The current study has several limitations. First, we only examine commuting ties, yet there are other ways that communities are connected (Velez et al. 2012; Sampson 2012; Graif et al. 2014; Papachristos et al. 2013; Schaefer 2012). The advantage of commuting ties is that they are a) directly related to the theoretical core of Wilson's point about the disappearance of work in inner city neighborhoods; b) they represent daily *routine* flows based on multiple residents—increasing the possibilities for social interaction and resource or information exchanges over space; and c) carry multiple potentially positive implications for the community, as noted below. In contrast, prior work focused on infrequent ties based on extreme actions (e.g., gang violence or co-offending). Still, commuting ties do not represent the full picture of beneficial ties between communities. Some types of ties, to political power for instance, may be infrequently activated but highly consequential for the community (e.g., avoiding a highway being built through the neighborhood). Future studies will benefit from expanding the definition of neighborhood ties.

The commuting data has strengths as well as limitations. The LODES data capture about 95% of formal salary and wage jobs (Graham et al. 2014), however gray and black market employment is not captured. Multiple worksite reports are included, reflecting more accurately than other employer data the information where workers report to more often. Still, when work is conducted at temporary locations, these locations may or may not be reported. To the extent that such data can be collected in the future, an important direction for research will be to explore whether individuals in such jobs could bridge dissimilar neighborhoods, otherwise disconnected.

Causal inference is in part bolstered by the longitudinal design, the lagged violence measurement, and the modeling of formation and dissolution as separate processes. Still, more research is needed to understand possible reverse causal direction and processes of inter-neighborhood tie sorting at the formation and dissolution stage. The current study focused on a single, large city. Future analyses of other cities and of metropolitan areas will be valuable.

Contributions and Implications

Urban sociologists and criminologists have long been interested in the extent to which neighborhood conditions are related to crime (Shaw and McKay 1942). The focus has been predominantly on *internal* processes of social isolation as measured through social disorganization, weakened neighborhood social fabric, and the disappearance of local jobs, institutions, and opportunities (Wilson 1987; 1996). This article highlights the importance of assessing neighborhood isolation in a broader way, relative to its connections to *extra-local* resources and neighborhoods in the city, and found that in Chicago, violence significantly predicted neighborhood disconnectedness.

This study's findings bring important first evidence to suggest that a) higher violence levels contribute to greater neighborhood isolation from the labor market in a large a Rust Belt city in the U.S. and that b) similarity in violence levels contributes to differential isolation, as reflected in homophilic connections. Only a few other studies have started to show a link between violence and patterns of inter-neighborhood connections across the city (Papachristos et al. 2013; Schaefer 2012), though they mainly focused on "negative" connections, like inter-gang conflicts or co-offending. The current study adds to this important thread and further extends it by defining ties more broadly. Moreover, extra-local labor market connections reflect many potentially positive interactions compared to offending ties. While criminals may use commuting channels to travel over space and commit crime outside their residential neighborhoods, many more positive resources and information can travel through the same channels, with the potential to improve the future of a violent community.

The current approach in defining ties adds to prior explorations of positive connections between neighborhoods based on individual daily mobility which emerged in important recent studies by Krivo et al. (2013) and Browning et al. (2015) based on residents traveling over space for work and other routine activities. We build on this work and further expand the literature by a) highlighting important connections between neighborhoods rather than between individuals, b) drawing on a census of ties rather than information from a sample of nodes, and c) investigating for the first time the role of violence on inter-neighborhood commuting networks.

This study's findings that violence contributes to neighborhood isolation and network homophily have several important implications. By increasing isolation and differential exclusion from non-violent and presumably more resourceful communities, violence proves to have an impact on neighborhoods far broader than the costs of crime incidents. First, commuting to only similar communities keeps violent neighborhoods in a cycle of deprivation, where fewer external resources (salary, loans, or crime control information) flow back than would to better connected neighborhoods. A community's violence and distress thus become amplified. An important study (Velez et al. 2012) found that weakened extra-neighborhood connections based on mortgage lending increase crime -- suggesting long term consequences for neighborhoods' development. External connections and the corresponding bridging social capital may provide violent neighborhoods with resources that reduce their crime rates.

Second, beyond inadequate access to jobs, residents may also have lowered access to other types of extra-local organizations and institutions including recreation centers, health services, and skills training. Isolation from jobs and other organizations and services may thus be symptomatic of a larger phenomenon of exclusion of distressed communities' residents from fully participating in urban life. Decreasing the isolation of violent neighborhoods may thus benefit communities on multiple dimensions. As community members gain connections throughout the city, particularly to people in advantaged neighborhoods, they may be able to affect the type of policy decisions that impact the spatial distribution of disadvantage across the city and reduce place inequalities (Logan and Molotch 1987).

Our findings are consistent with research in community psychology which shows that ties between diverse communities are less prevalent. Still, we are encouraged by recent explorations into the specific conditions under which such ties become possible and contribute to bridging social capital (Neal and Neal 2014; Neal 2015; Stivala 2016). Among the distressed and violent neighborhoods that are not disconnected from the larger network of city-wide resources, opportunities may open for resources and information relevant for crime control to travel back to the distressed communities. Some studies indicated that about half of non-kin ties are formed at work (Marks 1994), and ties at work are more heterogeneous on race and religion (Marsden 1990; Reskin et al. 1999). Such ties may provide access to a wider range of resources and information than the job alone implies.

Finding ways to encourage organizations and institutions to either locate in vulnerable communities or to connect from a distance to isolated communities has the potential to break the downward spiral of neighborhood violence and distress.

Policy makers may be concerned that improving connections between violent and non-violent communities may contribute to spreading violence across the city (Tita and Griffiths 2005; Bernasco and Kooistra 2010). Still, insights from a long line of work in social disorganization and public social control establish a clear foundation for expectations that neighborhoods with strong internal ties and strong connections to the city at large make for stable, low-crime communities. We thus would not expect connections between violent and non-violent communities to spread crime, but instead, to reduce it. Importantly, most residents of violent communities are not themselves violent or criminal, but they are generally disadvantaged and neighborhood isolation further disadvantages them. When choosing between containing crime and reducing crime, the latter seems the more obvious choice. More research is needed on the mechanisms underlying the link between violence and neighborhoods' structural isolation. Still, programs and policies that address employer discrimination based on neighborhood reputation, increase safety and access to transportation and health care for residents at high risk for violence injuries and trauma would likely go a long way toward addressing the problem.

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Appendix

Table A1

TERGM - Backbone (0.05) by different crime types

Formation Models	Model 1a - Violent crimes	Model 2a – Homicides	Model 3a - Robbery	Model 4a - Robbery and aggravated assault
Network structure				
Edge	-4.08 (0.15) ***	-3.88 (0.12) ***	-3.8 (0.14) ***	-3.77 (0.16) ***
Reciprocity	0.64 (0.12) ***	0.61 (0.12) ***	0.6 (0.12) ***	0.56 (0.13) ***
Geometrical weighted in-degree (popularity spread)	-1.34 (0.27) ***	-1.3 (0.25) ***	-1.28 (0.27) ***	-1.29 (0.28) ***
Receiver effects ("Work" community effects)				
Violent Crime Rate	2.59 (1.62)	-0.07 (0.23)	0.02 (0.01) †	0.13 (0.09)
Residential stability	-0.29 (0.05) ***	-0.28 (0.05) ***	-0.28 (0.05) ***	-0.3 (0.05) ***
Racial and ethnic diversity	-0.12 (0.05) *	-0.12 (0.05) *	-0.11 (0.05) *	-0.15 (0.06) **
Density of local jobs	0.24 (0.22)	0.12 (0.2)	0.17 (0.21)	0.2 (0.22)
Sender effects ("Home" community effects)				
Violent Crime Rate	5.55 (1.69) ***	0.23 (0.24)	0 (0.01)	0.06 (0.09)
Residential stability	0.74 (0.06) ***	0.71 (0.06) ***	0.7 (0.06) ***	0.67 (0.06) ***

Formation Models	**Model 1a - Violent crimes**	**Model 2a – Homicides**	**Model 3a - Robbery**	**Model 4a - Robbery and aggravated assault**
Racial and ethnic diversity	0.37 (0.06) ***	0.32 (0.06) ***	0.27 (0.06) ***	0.29 (0.06) ***
Density of local jobs	-0.34 (0.23)	-0.48 (0.2) *	-0.46 (0.23) *	-0.39 (0.23) †
Relational effects				
Spatial proximity	1.38 (0.13) ***	1.45 (0.12) ***	1.4 (0.13) ***	1.35 (0.14) ***
Transportation	0.21 (0.02) ***	0.22 (0.02) ***	0.21 (0.02) ***	0.21 (0.02) ***
Dissimilarity				
Violent Crime Rate	-11.03 (1.97) ***	-0.31 (0.25)	-0.07 (0.01) ***	-0.59 (0.11) ***
Residential stability	-0.3 (0.06) ***	-0.31 (0.06) ***	-0.32 (0.07) ***	-0.32 (0.07) ***
Racial and ethnic diversity	-0.53 (0.06) ***	-0.65 (0.06) ***	-0.58 (0.06) ***	-0.56 (0.06) ***
Density of local jobs	0.3 (0.24)	0.44 (0.21) *	0.45 (0.23) †	0.35 (0.24)
AIC	-738824	-738776	-738800	-590892
BIC	-738673	-738625	-738649	-590743
Dissolution Models	Model 1b - Violent crimes	Model 2b - Homicides	Model 3b - Robbery	Model 4b - Robbery and aggravated assault
Network structure				
Edge	0.56 (0.19) **	0.28 (0.16) .	0.56 (0.18) **	0.57 (0.19) **
Reciprocity	0.67 (0.13) ***	0.68 (0.14) ***	0.6 (0.14) ***	0.6 (0.15) ***
Geometrical weighted in-degree (popularity spread)	-0.91 (0.19) ***	-0.89 (0.2) ***	-0.83 (0.2) ***	-0.74 (0.21) ***
Receiver effects (“Work” community effects)				
Violent Crime Rate	-3.31 (2.1)	-0.53 (0.32) †	-0.03 (0.02) *	-0.24 (0.11) *
Residential stability	-0.22 (0.07) **	-0.23 (0.07) ***	-0.27 (0.07) ***	-0.2 (0.07) **
Racial and ethnic diversity	-0.12 (0.06) †	-0.1 (0.06)	-0.13 (0.06) *	-0.1 (0.07)
Density of local jobs	2.37 (0.25) ***	2.42 (0.26) ***	2.39 (0.25) ***	2.32 (0.25) ***
Sender effects (“Home” community effects)				
Violent Crime Rate	-10.7 (2.13) ***	-0.71 (0.29) *	-0.08 (0.01) ***	-0.62 (0.11) ***
Residential stability	0.14 (0.07) *	0.2 (0.07) **	0.18 (0.07) *	0.16 (0.07) *
Racial and ethnic diversity	0.12 (0.07) †	0.2 (0.06) **	0.11 (0.06) †	0.11 (0.07) †
Density of local jobs	-0.17 (0.23)	-0.13 (0.23)	-0.16 (0.23)	-0.28 (0.23)
Relational effects				
Spatial proximity	1.26 (0.12) ***	1.25 (0.12) ***	1.26 (0.12) ***	1.21 (0.13) ***
Transportation	0.02 (0.02)	0 (0.02)	0.03 (0.02)	0.04 (0.03)
Dissimilarity				
Violent Crime Rate	1.84 (2.57)	-0.84 (0.35) *	0 (0.02)	0.05 (0.14)
Residential stability	-0.12 (0.08)	-0.13 (0.08) †	-0.13 (0.08)	-0.12 (0.08)
Racial and ethnic diversity	-0.12 (0.08)	-0.06 (0.08)	-0.13 (0.08)	-0.17 (0.09) †
Density of local jobs	0.17 (0.24)	0.11 (0.25)	0.19 (0.25)	0.3 (0.24)

Formation Models	Model 1a - Violent crimes	Model 2a – Homicides	Model 3a - Robbery	Model 4a - Robbery and aggravated assault
AIC	3479	3488	3460	3167
BIC	3591	3599	3572	3276

Notes: Main cells represent ERGM estimates. Standard errors in parentheses. N = 77 nodes (community areas).

*** p < .001,

** p < .01,

* p < .05,

† p <.10

Table A2

TERGM additional controls

Formation Models	Model 1a Cut-off 0.005	Model 2a Backbone alpha 0.05
Network structure		
Edge	-4.1 (0.32) ***	-4.18 (0.27) ***
Reciprocity	-0.07 (0.17)	0.47 (0.11) ***
Geometrical weighted in-degree (popularity spread)	-5 (0.31) ***	-1.33 (0.27) ***
Receiver effects (“Work” community effects)		
Violent crime rate	-0.54 (2.43)	-1.87 (2.32)
Residential stability	-1.03 (0.08) ***	-0.33 (0.06) ***
Disadvantage	0.14 (0.1)	0.06 (0.09)
Race category (Base: White)		
Black	0.09 (0.25)	-0.96 (0.25) ***
Latino	-0.62 (0.2) **	-0.3 (0.2)
Mixed	-0.42 (0.18) *	0.1 (0.18)
Sender effects (“Home” community effects)		
Violent crime rate	13.02 (3.04) ***	-2.42 (2.43)
Residential stability	0.44 (0.08) ***	0.56 (0.06) ***
Disadvantage	-0.53 (0.12) ***	-0.15 (0.09)
Race category (Base: White)		
Black	-0.68 (0.23) **	-0.68 (0.22) **
Latino	-0.6 (0.2) **	0.03 (0.18)
Mixed	0.03 (0.17)	0.29 (0.17) †
Relational effects		
Spatial proximity	2.13 (0.15) ***	1.39 (0.12) ***
Transportation	0.11 (0.03) ***	0.18 (0.02) ***
Dissimilarity		
Violent crime rate	-11.85 (2.98) ***	-4.37 (2.44) †
Residential stability	0.3 (0.11) **	0.14 (0.09)
Disadvantage	-0.47 (0.09) ***	-0.39 (0.07) ***
Similarity		
White	0.36 (0.24)	-0.05 (0.27)

Formation Models	**Model 1a Cut-off 0.005**	**Model 2a Backbone alpha 0.05**
Black	0.68 (0.28) *	2.69 (0.25) ***
Latino	1.05 (0.3) ***	0.53 (0.3) †
Mixed	-0.23 (0.21)	-0.1 (0.21)
AIC	-741370	-738843
BIC	-741157	-738630

Dissolution Models	Model 1b Cut-off 0.005	Model 2b Backbone alpha 0.05
Network structure		
Edge	2.76 (0.33) ***	1.92 (0.31) ***
Reciprocity	0.21 (0.18)	0.45 (0.14) **
Geometrical weighted in-degree (popularity spread)	-1.69 (0.25) ***	-1.39 (0.19) ***
Receiver effects (“Work” community effects)		
Violent crime rate	28.72 (2.74) ***	20.94 (2.55) ***
Residential stability	-0.42 (0.09) ***	-0.59 (0.08) ***
Disadvantage	0.72 (0.11) ***	0.16 (0.1) †
Race category (Base: White)		
Black	-3.61 (0.29) ***	-1.96 (0.3) ***
Latino	-1.83 (0.21) ***	-1.32 (0.22) ***
Mixed	-1.51 (0.19) ***	-1.28 (0.21) ***
Sender effects (“Home” community effects)		
Violent crime rate	-15.68 (3.2) ***	-11.97 (2.77) ***
Residential stability	0.21 (0.09) *	0.27 (0.08) ***
Disadvantage	0.07 (0.11)	0.09 (0.11)
Race category (Base: White)		
Black	0.87 (0.28) **	0.86 (0.28) **
Latino	-0.22 (0.21)	0.24 (0.2)
Mixed	-0.14 (0.18)	-0.31 (0.19)
Relational effects		
Spatial proximity	0.41 (0.15) **	1.11 (0.13) ***
Transportation	0.13 (0.03) ***	0.03 (0.02)
Dissimilarity		
Violent crime rate	2.34 (2.95)	-1.47 (2.9)
Residential stability	-0.23 (0.1) *	-0.1 (0.1)
Disadvantage	-0.25 (0.11) *	-0.12 (0.09)
Similarity		
White	-0.26 (0.25)	0.39 (0.29)
Black	-0.81 (0.29) **	-1.54 (0.29) ***
Latino	-0.32 (0.32)	-1.13 (0.33) ***
Mixed	0.36 (0.23)	0.42 (0.24) †
AIC	3419	3630
BIC	3578	3788

Notes: Main cells represent ERGM estimates. Standard errors in parentheses. N = 77 nodes (community areas).

*** p < .001,

** p < .01,

* p < .05,

† p <.10

Table A3

TERGM different cut-offs

Formation Models	Model 1a Cut-off 0.0025	Model 2a Cut-off 0.0030	Model 3a Cut-off 0.010	Model 4a Backbone - alpha 0.01
Network structure				
Edge	-3.52 (0.13) ***	-3.62 (0.15) ***	-4.22 (0.31) ***	-4.92 (0.25) ***
Reciprocity	0.16 (0.1)	0.12 (0.12)	-3.12 (0.75) ***	0.32 (0.24)
Geometrical weighted in-degree (popularity spread)	-3.74 (0.31) ***	-3.48 (0.25) ***	-4.6 (0.34) ***	-1.47 (0.21) ***
Receiver effects ("Work" community effects)				
Violent crime rate	-3.93 (1.2) **	-3.31 (1.54) *	8.66 (2.84) **	9.56 (2.86) ***
Residential stability	-0.61 (0.04) ***	-0.59 (0.05) ***	-0.86 (0.19) ***	-0.34 (0.09) ***
Racial and ethnic diversity	-0.25 (0.04) ***	-0.3 (0.04) ***	-0.2 (0.11) †	-0.17 (0.09) †
Density of local jobs	4.34 (0.31) ***	3.25 (0.28) ***	0.33 (0.36)	0.74 (0.27) **
Sender effects ("Home" community effects)				
Violent crime rate	0.75 (1.42)	-3.75 (1.72) *	-4.81 (3.7)	-8.59 (3.16) **
Residential stability	0.22 (0.05) ***	0.27 (0.05) ***	0.82 (0.21) ***	0.59 (0.09) ***
Racial and ethnic diversity	0.02 (0.05)	0.08 (0.05)	0.26 (0.12) *	0.36 (0.1) ***
Density of local jobs	1.69 (0.31) ***	1.22 (0.27) ***	0.09 (0.37)	-0.18 (0.28)
Relational effects				
Spatial proximity	0.8 (0.14) ***	1.17 (0.15) ***	1.41 (0.27) ***	2.59 (0.19) ***
Transportation	0.29 (0.03) ***	0.27 (0.03) ***	0.28 (0.05) ***	0.02 (0.03)
Dissimilarity				
Violent crime rate	-3.98 (1.49) **	-4.19 (1.77) *	-2.46 (3.62)	-8.35 (3.49) *
Residential stability	-0.23 (0.05) ***	-0.18 (0.05) ***	-0.76 (0.22) ***	-0.06 (0.1)
Racial and ethnic diversity	-0.26 (0.05) ***	-0.11 (0.05) *	-0.26 (0.12) *	-0.67 (0.11) ***
Density of local jobs	-1.72 (0.31) ***	-1.2 (0.27) ***	0.17 (0.39)	0.34 (0.29)
AIC	-463210	-594497	-741753	-740628
BIC	-46306	-594349	-741601	-740476

Dissolution models	Model 1b Cut-off 0.0025	Model 2b Cut-off 0.0030	Model 3b Cut-off 0.010	Model 4b Backbone - alpha 0.01
Network structure				
Edge	0.92 (0.15) ***	1.18 (0.16) ***	-0.36 (0.46)	0.91 (0.36) *
Reciprocity	0.01 (0.11)	0.2 (0.12) †	2.23 (2.59)	1.47 (0.27) ***
Geometrical weighted in-degree (popularity spread)	-2.47 (0.28) ***	-1.82 (0.25) ***	-1.98 (0.42) ***	-1.12 (0.29) ***
Receiver effects ("Work" community effects)				
Violent crime rate	-3.78 (1.65) *	-6.13 (1.83) ***	6.18 (5.09)	-19.31 (4.22) ***

Formation Models	Model 1a Cut-off 0.0025	Model 2a Cut-off 0.0030	Model 3a Cut-off 0.010	Model 4a Backbone - alpha 0.01
Residential stability	-0.35 (0.05) ***	-0.52 (0.05) ***	0.06 (0.25)	-0.32 (0.13) *
Racial and ethnic diversity	-0.1 (0.05) *	-0.11 (0.05) *	0.07 (0.17)	-0.1 (0.12)
Density of local jobs	1.92 (0.24) ***	0.91 (0.17) ***	1.81 (0.41) ***	2.59 (0.4) ***
Sender effects (“Home” community effects)				
Violent crime rate	-4.55 (1.42) **	-3.99 (1.59) *	-3.98 (3.72)	8.01 (3.51) *
Residential stability	0.17 (0.05) **	0.15 (0.06) *	-1 (0.35) **	0.31 (0.12) **
Racial and ethnic diversity	0.17 (0.05) ***	0.18 (0.05) ***	-0.18 (0.14)	0.19 (0.11) †
Density of local jobs	0.32 (0.24)	-0.07 (0.16)	0.01 (0.31)	-0.14 (0.31)
Relational effects				
Spatial proximity	1.05 (0.12) ***	1.19 (0.13) ***	1.17 (0.35) ***	0.64 (0.25) *
Transportation	0.21 (0.02) ***	0.16 (0.02) ***	0.11 (0.05) *	0.08 (0.04) *
Dissimilarity				
Violent crime rate	-4.5 (1.62) **	-0.65 (1.86)	-2.13 (4.8)	4.14 (4.93)
Residential stability	0.06 (0.05)	0.02 (0.06)	0.93 (0.35) **	-0.46 (0.13) ***
Racial and ethnic diversity	0.04 (0.05)	-0.18 (0.05) **	-0.02 (0.17)	-0.27 (0.15) †
Density of local jobs	-0.29 (0.24)	0.07 (0.16)	-0.28 (0.34)	-0.1 (0.32)
AIC	5903	5538	1131	1373
BIC	6024	5658	1233	1476

Notes: Main cells represent ERGM estimates. Standard errors in parentheses. N = 77 nodes (community areas).

*** $p < .001$,

** $p < .01$,

* $p < .05$,

† $p < .10$.

The model with cut-off 0.0025 includes only 2002-2011 period. The model with cut-off 0.0030 includes only 2003-2011 period.

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Highlights

- We examined violence effects on external social isolation of urban neighborhoods.
- Commuting networks among Chicago's neighborhoods were analyzed over twelve years.
- Violence predicted residential neighborhood isolation from the citywide network.
- Similarity in violence predicted inter-neighborhood ties, indicating homophily.
- Violence homophily affected tie formation; neighborhood violence dissolved ties.

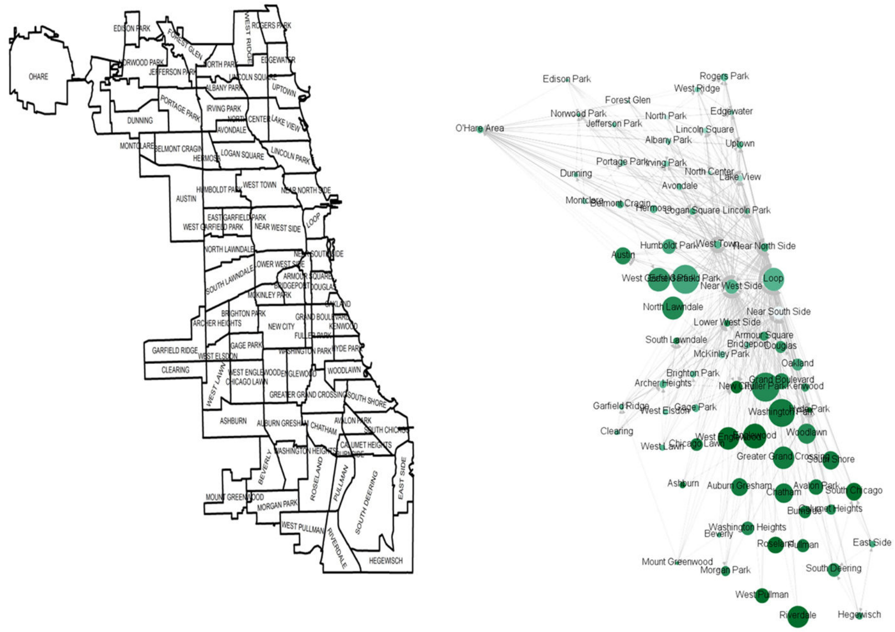

Fig. 1.

Network isolation and violence among Chicago's neighborhoods. *Leftmost map*: Geographic map of all 77 neighborhoods' (community areas) boundaries. *Rightmost map*: Commuting network (binary ties) among neighborhoods (represented by nodes, circles of various size, positioned at neighborhoods' geographic centroid). The more violent the neighborhood, the larger size of the node. The more isolated the neighborhood (inverse out-degree), the darker the color.

Fig. 2.

Homophily and violence in Chicago's inter-neighborhood commuting network. The more violent the neighborhood, the larger size of nodes. The more isolated (inverse out-degree) the neighborhood, the darker the color.

Table 1

Descriptives and correlations

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1 Violent crime rate (2001)	0.05	0.04	0.01	0.16											
2 Violent crime rate (2012)	0.03	0.02	0.00	0.1	-										
3 Population density	5.39	2.81	0.43	14	-0.21	-0.23									
4 Disadvantage	-0.04	0.91	-1.24	2.38	0.91	0.80	-0.16								
5 Residential stability	-0.01	0.97	-2.11	1.73	0.00	0.11	-0.63	0.08							
6 Racial and ethnic diversity	0.12	1.04	-1.54	2.4	-0.59	-0.59	0.39	-0.54	-0.38						
7 Density of local jobs (2002)	0.35	1.40	0.02	12.18	-0.13	-	0.10	-0.33	-0.45	0.12					
8 Density of local jobs (2013)	0.36	1.59	0.02	13.85	-	0.03	0.02	-0.28	-0.38	0.06	0.96				
9 Out-degree (2002)	8.3	2.72	2	14	-0.49	-0.14	-0.54	0.10	0.56	-0.05	-				
10 In-degree (2002)	8.3	16.81	0	76	0.03	-	0.10	-0.14	-0.50	0.03	0.76	-	-0.12		
11 Out-degree (2013)	6.82	2.61	3	15	-	-0.59	0.25	-0.57	-0.37	0.59	-	0.13	-	-	
12 In-degree (2013)	6.82	16.26	0	76	-	-0.02	0.13	-0.22	-0.51	0.04	-	0.78	-	-	0.14

N = 77 community areas

Table 2

ERGM Results

	2002					2005	2009	2013
	Model1	Model2	Model3	Model4	Model5	Model5	Model5	Model5
Network structure								
Edge	-1.51 (0.08) ***	-1.58 (0.08) ***	-3.4 (0.19) ***	-3.34 (0.19) ***	-2.75 (0.28) ***	-2.8 (0.27) ***	-2.65 (0.3) ***	-2.81 (0.33) ***
Reciprocity	0.24 (0.18)	-0.46 (0.2) *	0.00 (0.29)	0.03 (0.29)	0.00 (0.3)	0.26 (0.31)	-0.06 (0.35)	-0.73 (0.35) *
Geometrical weighted in-degree (popularity spread)	-11.51 (0.53) ***	-10.66 (0.55) ***	-4 (0.44) ***	-3.96 (0.45) ***	-3.88 (0.46) ***	-4.26 (0.47) ***	-3.64 (0.46) ***	-4.20 (0.53) ***
Receiver effects (“Work” community effects)								
Violent crime rate	4.67 (0.87) ***	1.62 (1.06)	-8.39 (1.83) ***	-5.54 (1.98) **	-7.07 (2.05) ***	-13.07 (2.46) ***	-10.88 (3.18) ***	-14.11 (4.63) **
Residential stability			-0.65 (0.08) ***	-0.65 (0.07) ***	-0.82 (0.11) ***	-0.83 (0.11) ***	-0.63 (0.11) ***	-0.8 (0.12) ***
Racial and ethnic diversity			-0.32 (0.07) ***	-0.34 (0.07) ***	-0.39 (0.07) ***	-0.48 (0.07) ***	-0.37 (0.08) ***	-0.34 (0.08) ***
Density of local jobs			3.33 (0.15) ***	3.38 (0.16) ***	3.7 (0.33) ***	3.4 (0.31) ***	3.72 (0.35) ***	3.52 (0.41) ***
Sender effects (“Home” community effects)								
Violent crime rate	-4.75 (1.38) ***	-8.12 (1.44) ***	-7.61 (2.40) **	-5.67 (2.56) *	-7.11 (2.67) **	-3.9 (2.85)	-8.74 (3.39) **	-18.21 (4.87) ***
Residential stability			0.38 (0.09) ***	0.37 (0.09) ***	0.54 (0.11) ***	0.66 (0.12) ***	0.48 (0.12) ***	0.16 (0.13)
Racial and ethnic diversity			0.37 (0.09) ***	0.36 (0.09) ***	0.33 (0.1) ***	0.35 (0.09) ***	0.18 (0.09) †	0.2 (0.09) *
Density of local jobs			-0.07 (0.06)	-0.06 (0.06)	0.34 (0.32)	0.5 (0.31)	0.61 (0.36) †	0.94 (0.42) *
Relational effects								
Spatial proximity	1.99 (0.14) ***	1.12 (0.17) ***	2.37 (0.22) ***	2.33 (0.21) ***	2.24 (0.22) ***	2.09 (0.22) ***	1.49 (0.25) ***	2.3 (0.26) ***
Transportation		0.36 (0.03) ***	0.42 (0.04) ***	0.39 (0.04) ***	0.38 (0.04) ***	0.36 (0.04) ***	0.36 (0.04) ***	0.35 (0.05) ***
Dissimilarity								
Violent crime rate	-10.06 (1.65) ***	-6.67 (1.82) ***		-8.45 (2.61) **	-6.63 (2.79) *	-6.71 (2.94) *	-7.68 (3.8) *	-6.4 (5.45)
Residential stability					-0.34 (0.12) **	-0.24 (0.13) †	-0.18 (0.13)	-0.04 (0.14)
Racial and ethnic diversity					-0.25 (0.09) **	-0.13 (0.09)	-0.26 (0.1) **	-0.25 (0.11) *
Density of local jobs					-0.42 (0.33)	-0.47 (0.31)	-0.52 (0.35)	-0.88 (0.42) *
AIC	3213	3014	1782	1773	1760	1786	1576	1486
BIC	3260	3067	1869	1867	1874	1900	1689	1600

Notes: Main cells represent ERGM estimates. Standard errors in parentheses. N = 77 nodes (community areas).

*** $p < .001$,

** $p < .01$,

* $p < .05$,

† $p < .10$

Table 3

TERGM models – violent crime rate

Formation Models	Model 1a	Model 2a	Model 3a	Model 4a	Model 5a
Network structure					
Edge	-3.83 (0.09) ***	-3.82 (0.09) ***	-4.63 (0.14) ***	-4.6 (0.14) ***	-4.15 (0.18) ***
Reciprocity	0.17 (0.13)	-0.12 (0.13)	0.11 (0.16)	0.1 (0.17)	0.07 (0.17)
Geometrical weighted in-degree (popularity spread)	-5.21 (0.28) ***	-5.13 (0.3) ***	-4.07 (0.25) ***	-4.12 (0.28) ***	-4.09 (0.29) ***
Receiver effects (“Work” community effects)					
Violent crime rate	9.57 (1.53) ***	6.89 (1.64) ***	1.77 (1.53)	4.29 (1.79) *	3.36 (1.84) †
Residential stability			-0.7 (0.06) ***	-0.7 (0.05) ***	-0.84 (0.07) ***
Racial and ethnic diversity			-0.28 (0.05) ***	-0.29 (0.05) ***	-0.3 (0.06) ***
Density of local jobs			1.1 (0.1) ***	1.1 (0.1) ***	1.32 (0.19) ***
Sender effects (“Home” community effects)					
Violent crime rate	-1.17 (1.62)	-3.26 (1.7) †	-3.17 (1.91) †	0.78 (2.16)	-0.75 (2.11)
Residential stability			0.33 (0.06) ***	0.31 (0.06) ***	0.47 (0.08) ***
Racial and ethnic diversity			0.25 (0.06) ***	0.24 (0.06) ***	0.19 (0.06) **
Density of local jobs			0.06 (0.03) †	0.07 (0.03) †	0.41 (0.2) *
Relational effects					
Spatial proximity	2.21 (0.11) ***	1.62 (0.14) ***	2.05 (0.15) ***	2.01 (0.16) ***	1.97 (0.15) ***
Transportation		0.19 (0.03) ***	0.21 (0.03) ***	0.19 (0.03) ***	0.17 (0.03) ***
Dissimilarity					
Violent crime rate	-9.73 (2.05) ***	-7.6 (2.09) ***		-9.41 (2.14) ***	-7.76 (2.21) ***
Residential stability					-0.29 (0.08) ***
Racial and ethnic diversity					-0.15 (0.06) *
Density of local jobs					-0.33 (0.2)
AIC	-740963	-741016	-741366	-741392	-741406
BIC	-740901	-740945	-741250	-741268	-741255
Dissolution Models	Model 1b	Model 2b	Model 3b	Model 4b	Model 5b

Formation Models	Model 1a	Model 2a	Model 3a	Model 4a	Model 5a
Network structure					
Edge	1.76 (0.11) ***	1.71 (0.11) ***	0.93 (0.16) ***	0.92 (0.15) ***	1.17 (0.2) ***
Reciprocity	0.33 (0.14) *	0.03 (0.14)	0.02 (0.17)	0.03 (0.17)	0 (0.18)
Geometrical weighted in-degree (popularity spread)	-2.45 (0.21) ***	-2.29 (0.21) ***	-1.5 (0.22) ***	-1.51 (0.22) ***	-1.55 (0.23) ***
Receiver effects (“Work” community effects)					
Violent crime rate	11.72 (2.06) ***	9.94 (2.09) ***	-6.14 (2.32) **	-6.44 (2.32) **	-7.49 (2.48) **
Residential stability			-0.31 (0.07) ***	-0.31 (0.07) ***	-0.31 (0.08) ***
Racial and ethnic diversity			-0.15 (0.06) *	-0.15 (0.06) *	-0.19 (0.06) **
Density of local jobs			1.36 (0.12) ***	1.36 (0.13) ***	1.26 (0.2) ***
Sender effects (“Home” community effects)					
Violent crime rate	-7.25 (1.56) ***	-9.18 (1.64) ***	-6.32 (1.8) ***	-7.12 (2.03) ***	-7.39 (2.04) ***
Residential stability			0.01 (0.07)	0.01 (0.07)	-0.05 (0.09)
Racial and ethnic diversity			0.1 (0.06) †	0.11 (0.06) †	0.14 (0.06) *
Density of local jobs			-0.01 (0.04)	-0.01 (0.04)	-0.11 (0.17)
Relational effects					
Spatial proximity	0.23 (0.12) †	-0.14 (0.14)	0.66 (0.14) ***	0.67 (0.14) ***	0.66 (0.15) ***
Transportation		0.13 (0.02) ***	0.13 (0.03) ***	0.13 (0.03) ***	0.12 (0.03) ***
Dissimilarity					
Violent crime rate	3.27 (2.28)	4.73 (2.25) *		2.24 (2.49)	3.67 (2.47)
Residential stability					0.04 (0.09)
Racial and ethnic diversity					-0.24 (0.08) **
Density of local jobs					0.09 (0.18)
AIC	3911	3869	3504	3505	3501
BIC	3957	3922	3590	3598	3614

Notes: Main cells represent ERGM estimates. Standard errors in parentheses. N = 77 nodes (community areas).

*** $p < .001$,

** $p < .01$,

* $p < .05$,

† p <.10

Table 4

TERGM models - Different crime types

Formation Models	**Model 1a -Homicides**	**Model 2a -Robbery**	**Model 3a - Robbery and aggravated assault**
Network structure			
Edge	-4.07 (0.17) ***	-4.01 (0.17) ***	-3.84 (0.19) ***
Reciprocity	0.05 (0.17)	0 (0.18)	-0.02 (0.19)
Geometrical weighted in-degree (popularity spread)	-4.07 (0.28) ***	-4.09 (0.26) ***	-4.06 (0.27) ***
Receiver effects (“Work” community effects)			
Violent Crime Rate	0.48 (0.33)	0.03 (0.01) †	0.15 (0.1)
Residential stability	-0.84 (0.07) ***	-0.83 (0.07) ***	-0.82 (0.08) ***
Racial and ethnic diversity	-0.29 (0.05) ***	-0.29 (0.05) ***	-0.32 (0.06) ***
Density of local jobs	1.29 (0.21) ***	1.28 (0.21) ***	1.15 (0.23) ***
Sender effects (“Home” community effects)			
Violent Crime Rate	-0.9 (0.36) *	-0.04 (0.02) *	-0.27 (0.12) *
Residential stability	0.47 (0.08) ***	0.45 (0.08) ***	0.45 (0.08) ***
Racial and ethnic diversity	0.18 (0.06) **	0.14 (0.06) *	0.14 (0.06) *
Density of local jobs	0.31 (0.21)	0.32 (0.21)	0.25 (0.24)
Relational effects			
Spatial proximity	1.98 (0.15) ***	1.98 (0.15) ***	2.01 (0.15) ***
Transportation	0.19 (0.03) ***	0.18 (0.03) ***	0.18 (0.03) ***
Dissimilarity			
Violent Crime Rate	-0.37 (0.39)	-0.05 (0.02) *	-0.4 (0.13) **
Residential stability	-0.29 (0.09) ***	-0.29 (0.08) ***	-0.28 (0.09) **
Racial and ethnic diversity	-0.21 (0.06) ***	-0.18 (0.06) **	-0.21 (0.06) ***
Density of local jobs	-0.25 (0.21)	-0.21 (0.21)	-0.14 (0.24)
AIC	-741410	-741413	-593211
BIC	-741259	-741262	-593062
Dissolution Models	Model 1b -Homicides	Model 2b -Robbery	Model 3b - Robbery and aggravated assault
Network structure			
Edge	0.89 (0.18) ***	0.87 (0.2) ***	0.74 (0.21) ***
Reciprocity	0.04 (0.18)	0.04 (0.18)	-0.06 (0.19)
Geometrical weighted in-degree (popularity spread)	-1.56 (0.23) ***	-1.55 (0.23) ***	-1.49 (0.24) ***
Receiver effects (“Work” community effects)			
Violent Crime Rate	-1.15 (0.37) **	-0.01 (0.02)	-0.01 (0.15)
Residential stability	-0.31 (0.08) ***	-0.36 (0.08) ***	-0.34 (0.08) ***
Racial and ethnic diversity	-0.18 (0.06) **	-0.16 (0.06) *	-0.17 (0.07) *

Formation Models	Model 1a -Homicides	Model 2a -Robbery	Model 3a - Robbery and aggravated assault
Density of local jobs	1.19 (0.2) ***	1.2 (0.2) ***	1.22 (0.21) ***
Sender effects ("Home" community effects)			
Violent Crime Rate	-0.81 (0.34) *	-0.04 (0.01) **	-0.39 (0.11) ***
Residential stability	-0.01 (0.09)	-0.04 (0.09)	-0.11 (0.1)
Racial and ethnic diversity	0.2 (0.06) ***	0.15 (0.06) *	0.13 (0.06) *
Density of local jobs	-0.09 (0.17)	-0.04 (0.17)	0.02 (0.18)
Relational effects			
Spatial proximity	0.69 (0.14) ***	0.69 (0.15) ***	0.77 (0.16) ***
Transportation	0.11 (0.03) ***	0.11 (0.03) ***	0.12 (0.03) ***
Dissimilarity			
Violent Crime Rate	0.35 (0.4)	0 (0.02)	0.04 (0.15)
Residential stability	0.04 (0.09)	0.06 (0.09)	0.13 (0.1)
Racial and ethnic diversity	-0.22 (0.07) **	-0.2 (0.07) **	-0.2 (0.08) **
Density of local jobs	0.06 (0.18)	0.04 (0.18)	-0.02 (0.19)
AIC	3511	3517	3208
BIC	3624	3630	3319

Notes: Main cells represent ERGM estimates. Standard errors in parentheses. N = 77 nodes (community areas).

*** p < .001,

** p < .01,

* p < .05,

† p <.10