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# Tragic, but not random: The social contagion of nonfatal gunshot injuries

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ABSTRACT

This study investigates the concentration of nonfatal gunshot injuries within risky social networks. Using six years of data on gunshot victimization and arrests in Chicago, we reconstruct patterns of co-offending for the city and locate gunshot victims within these networks. Results indicate that 70 percent of all nonfatal gunshot victims during the observation period can be located in co-offending networks comprised of less than 6 percent of the city's population. Results from logistic regression models suggest that as an individual's exposure to gunshot victims increases, so too do that individual's odds of victimization. Furthermore, even small amounts of exposure can dramatically increase the odds of victimization. For instance, every 1 percent increase in exposure to gunshot victims in one's immediate network increases the odds of victimization by roughly 1.1 percent, holding all else constant. These observed associations are more pronounced for young minority males, and effects of exposure extend to indirect network ties at distances of two to three steps removed. These findings imply that the risk of gunshot victimization is more concentrated than previously thought, being concentrated in small and identifiable networks of individuals engaging in risky behavior, in this case criminal activity.

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## 1. Introduction

Tragic acts of violence like the Sandy Hook shooting in Newtown, CT or the slaying of 15-year old Hadiya Pendleton in Chicago, IL redirect political and public attention towards gun violence. And, indeed, gun violence remains a pervasive problem. In 2010, the gun homicide rate in the United States (3.2 per 100,000) was more than three times higher than other industrialized democracies such as France (0.22), the United Kingdom (0.04), Canada (0.50), and Australia (0.09) and more akin to rates in countries such as Argentina (3.0), Uruguay (3.2), and Zimbabwe (4.7) (UNODC, 2011). Each year, more than 10,000 people in the U.S. are shot and killed by another person, and another 60,000 are treated for non-fatal gunshot injuries caused by assaults (CDC, 2012).

Statistics like these and images of innocent victims fuel the notion that violence is both pervasive and random. If gun violence can happen in an elementary school classroom or to an innocent adolescent girl standing in a public park with her friends, it can happen anywhere or to anyone. Yet tragic as these events and statistics are, gun violence is far from random. Gun violence is highly concentrated among particular segments of the population and in particular places. Young, minority males between the ages of 18–24 are the most likely victims of gun homicide, with rates of gun homicide more than fifty times higher than the overall U.S. average and ten times higher than white men in the same age range (Harper et al., 2007; Heron, 2007). Gun homicide also concentrates in small geographic areas within major U.S. cities, especially socially and economically disadvantaged neighborhoods (Braga et al., 2010; Jones-Webb and Wall, 2008; Peterson and Krivo, 2010; Weisburd et al., 2004).

While this uneven distribution by race and place provides insight into factors associated with elevated rates of victimization, it may inadvertently mask further disparities in individual risk. Cohort and cross-sectional studies consistently find that both violent victimization and offending tend to occur within small segments of populations of individuals actively engaged in delinquent and criminal activities (Kennedy, 1996; Loeber and Farrington, 2011; Thornberry et al., 2003; Wolfgang, 1958). Social network studies confirm such findings and further suggest that such populations are (a) fairly homogenous along traditional risk factors, (b) smaller than previously thought, and (c) readily identifiable through observational data (Papachristos et al., 2012a; Papachristos and Wildeman, 2014). Studies such as these imply that while risk factors play an important role in describing the distribution of gun

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violence across populations and places, they fare less well in explaining individual victimization or the concentration of violence within networks. In other words, our current explanations cannot explain why a specific young African American male in a high crime neighborhood becomes a murder victim while another young man with the identical risk factors does not. By failing to incorporate social networks into the analysis of gunshot victimization, we significantly misestimate the risk of victimization for individuals with seemingly identical risk factors.

Such a misestimation of the risk of gunshot injuries stems from two limitations: the overreliance on homicide data and the neglect of social networks. First, prior research relies almost exclusively on the analysis of gun homicides. Although homicide data tends to be extremely accurate because of the presence of an actual body and the amount of resources expended on homicide investigations, they are, statistically speaking, rare events. In fact, as the figures above suggest, there are roughly six non-fatal gunshot injuries for each gunshot homicide in the U.S. And, while research firmly establishes that gun homicides contribute to severe trauma and a host of negative health, educational, social, and economic outcomes for families and communities (Buka et al., 2001; Osofsky, 1999; Sharkey, 2010; Sharkey et al., 2012), very little research examines similar consequences and correlates of nonfatal gunshot injuries.

There is at least one other significant reason to more fully consider non-fatal gunshot injuries. On the most basic level, those who are shot but not killed represent an important—and dramatically understudied—vulnerable population within the public health community. Most directly, gunshot injuries account for significant reductions in life expectancy. According to one estimate, firearm injuries are responsible for a 151-day reduction in life expectancy for white males and a nearly one year (362-day) reduction in life expectancy for black males (Lemaire, 2005). In addition, nonfatal gunshot injuries reduce overall quality of life and contribute to sustained chronic health conditions. In a revealing ethnography of gunshot survivors in Philadelphia, Lee (2012) details the physical and mental health costs associated with gunshot injuries, including: physical disfigurement and disability, severe depression and anxiety, loss of employment, and long-term negative health consequences. For example, gunshot wounds to the abdomen can fundamentally transform how survivors perform basic bodily functions like the "ability to control and regulate how and where one defecates (or not)" and basic sexual functioning (Lee, 2012, pg. 249). Half of all the men interviewed by Lee (2012) lived with bullets or bullet fragments permanently lodged in their bodies that caused debilitating pain, stress, and anxiety that interfered with work and personal life. Effects such as these imply that the true cost of gun injuries, whatever that might be, greatly exceeds estimates obtained purely from homicide data.

Second, underestimation of the concentration of gun violence and individual risk of victimization may result from the failure to consider the importance of social networks. Despite the impression left by mass shootings that gun violence is perpetrated by strangers, nearly two-thirds of all gun homicides occur between individuals who know each other, suggesting that the context of social relationships is important in understanding the dynamics of gun violence (Decker, 1993; Smith and Zahn, 1999; Wilson, 1993). Recent network studies of gun violence in high crime communities underscore this point by demonstrating that the majority of gun homicides and non-fatal shootings occur within small, identifiable networks of individuals actively engaged in criminal and delinquent behavior (Papachristos et al., 2012a; Papachristos and Wildeman, 2014). For example, a study of one high-crime neighborhood in Boston found that 85 percent of all gunshot injuries occurred within a single network containing only 763 individuals—less than 2 percent of that community's population—a third of whom were gang members and a third of whom had an arrest in the months leading up to their victimization (Papachristos et al., 2012a). However, we know very little about how the contours of networks actually shape the risk of victimization, as this research is still in its infancy.

Focusing on non-fatal gunshot victims may also shed light on the reasons *why* gun violence concentrates within these networks. The clustering of gunshot victims in networks of active offenders demonstrates that the victims themselves are engaged in risky behaviors conducive to violence. The same is probably also true of the offenders, as victim and perpetrator are virtually indistinguishable along standard risk indicators and criminal histories (Berg et al., 2012; Braga, 2003). Gun assaults and homicides are the end result of dynamic interactional process between two (or more) individuals, and, indeed, the "victim" is the individual who received the injury but may in fact have been the instigator of the interaction (Luckenbill, 1977; Miethe and Regoeczi, 2004). If gunshot survivors continue to engage in the risky behaviors that placed them in the network in which they were victimized, then it is possible that they may also continue to engage in violent behavior that places others at risk of victimization. In short, they may very well "pass on" violence within their networks—a process consistent with qualitative research on the norms of retaliation and respect among males in high-crime communities (Anderson, 1999; Fagan and Wilkinson, 1998; Jacobs and Wright, 2006). As a case in point, a recent study of gang networks in Chicago and Boston finds that gang homicides are driven by norms of retaliation, organizational memory, status seeking behaviors, and other network processes (Papachristos et al., 2013). In the case of homicide, the victim is deceased, and the group seeks retaliation. The survival of gunshot victims may amplify such processes.

The present study has two objectives. First, we analyze the distribution of non-fatal gunshot injuries across high-risk networks in the entire city of Chicago. More specifically, we determine the extent to which non-fatal gunshot injuries concentrate and cluster within networks of individuals involved in risky behaviors, in this case incidents of co-involvement in a crime that leads to an arrest. We maintain that co-offending networks provide conservative estimates of the types of risky behavior that heightens an individual's exposure to situations, behaviors, and people that might elevate the probability of victimization. To date such studies rely on small samples or data for a single community (Papachristos et al., 2012a; Papachristos and Wildeman, 2014). Our study is the first to examine such networks for the entire co-offending population of a city and, thus, provide more accurate estimates of the true distribution of risk in a large city and over an extended period of time.

Our second objective is to assess whether or not the distribution of gunshot injuries in co-offending networks is associated with processes of *social contagion*—the extent to which one's probability of victimization is related to direct and indirect exposure to gunshot victims in one's social network. Other risky health behaviors—such as smoking (Christakis and Fowler, 2008; Mercken et al., 2009), alcohol and substance abuse (Fujimoto and Valente, 2012; Russell et al., 2002), obesity (Christakis and Fowler, 2007), and contracting an STD (adams et al., 2013; Morris, 1993)—are susceptible to peer influence. There are several reasons why gunshot victimization might be related to risky social networks. First, as just described, gun violence tends to concentrate within small groups and populations of active offenders (Braga, 2003; Papachristos et al., 2012a). Although we know little about the network structure of co-offending populations, group processes and peer influence have long been associated with the facilitation of crime and delinquency above and beyond individual selection (Warr, 2002). Second, norms surrounding gun use and gun carrying are associated with interactive and performative aspects of social life,

especially status enhancing behaviors (Fagan and Wilkinson, 1998; Wilkinson and Fagan, 1996). In particular, gangs and other delinquent groups often exert strong influence on violent offending and victimization, including gun carrying and gun use (Bjerregaard and Lizotte, 1995; Lizotte et al., 2000). Third, guns are durable goods, and acquiring a gun, especially illegally, requires knowledge and access to formal and informal networks and markets (Cook et al., 2007). Despite all of these reasons to expect social contagion processes in non-fatal gunshot injuries and growing interest in social network analysis in the study of public health, no study has yet to employ formal network models to ascertain if the distribution of gunshot injuries in an entire population is related to processes of peer influence or social contagion.

## 2. Data

Our analyses employ two sources of data recorded by the Chicago Police Department: records of non-fatal gunshot victims and incident-level arrest data. Data on non-fatal gunshot injuries are used to determine our main dependent variable of interest, whether or not an individual is a gunshot victim (1 = yes). These records include information on 10,814 individuals who were victims of non-fatal gunshot injuries reported to the police between January 1, 2006 and September 30, 2012. Consistent with our argument that gun violence is related to risky behaviors, the vast majority of gunshot victims (approximately 80 percent or $N = 8669$) had at least one prior arrest during that *same time period* unrelated to the shooting incident.

Incident-level arrest records are used to create co-offending networks and include 967,453 arrests that occurred between January 1, 2006 and September 30, 2012. In total, 1,247,278 arrests are recorded for this time period, but 22 percent (280,485) contained missing data and are subsequently dropped from the analysis. Records contain information on each arrest including victim and offender demographic information, type of crime, geographic location of each event, and police identified gang membership of the offender.

We use these data to create networks by first identifying all unique individuals in the arrest records and then identifying all instances of *co-offending*: incidents in which two or more individuals were arrested for involvement in the same crime. In total, 418,032 unique individuals were identified in the arrest records, of which 41 percent ($N = 169{,}725$) were arrested in an incident involving two or more individuals. In total, 35 percent of all arrest events ($N = 336{,}416$) involved more than one offender.

After identifying all unique individuals and incidents of co-offending, we create a person-by-event (two-mode) matrix that links each individual to a specific co-arrest. Then, we convert the person-by-event network to a binary person-by-person (one-mode) matrix based on the assumption that individuals engaging in a crime together are associated with each other or, more precisely, that they engage in risky behavior together. This type of two-mode to one-mode transformation in network analysis is commonly employed when the focus is (a) on one type of the social entities, in this case, the individuals, and (b) these primary actors are connected *via* the event in question (Borgatti and Everett, 1997). This procedure links individuals *through* events, where the resulting ties in the one-mode network are binary indicators of whether or not two individuals were ever co-arrested together during the observation period (1 = yes, 0 = no).

We dichotomize the co-offending matrix for two reasons. First, the vast majority of co-arrest cells (95 percent) represent a single event between individuals—a finding consistent with prior research on co-offending networks (McGloin and Piquero, 2010). Second, in the remaining 5 percent of cells we cannot distinguish between (a) arrests involving *multiple charges* between the same individuals during the same incident, and (b) repeated arrest events between the same individuals at different points in time. Type (a) would lead to a cell value greater than one, but, might be a false indicator of "tie strength"—i.e., we do not consider the severity of offense to be indicative of the strength of the relationship between individuals. In contrast, type (b) might very well be indicative of a stronger relationship between individuals that would be represented in a cell value greater than one. Because we are unable to differentiate between these two instances, we err on the conservative side so as to assume, at a minimum, any instance of co-offending represents only that two individuals "know" each other and have engaged in at least one risky behavior together. Creating networks in this way further provides a conservative estimate of the true underlying network since it captures only those incidents reported or observed by the police and that subsequently lead to an arrest.

Co-offending networks such as those used here represent a specific definition of risk. Most research on networks and health focuses on either social networks (e.g., friendship or kinship) or behavior networks (e.g., needle-sharing or sexual relations). While co-offending is technically an example of the latter, crime itself is a social phenomenon, and violence is most likely to occur between people who know each other prior to the event (Luckenbill, 1977; Miethe and Regoeczi, 2004). As such, the types of behaviors that result in a co-arrest imply that these individuals know each other outside of a single event—i.e., one is likely to engage in crime with someone they know. For example, a recent network survey of active offenders in Chicago found that, on average, 48 percent of all reported criminal ties (such as co-offending) extended to non-criminal social activities including social, financial, and emotional support and activities (Papachristos et al., 2012b). While we are unable to ascertain the extent to which individuals in the present study know each other outside of the specified co-arrest, we maintain that engaging in criminal behaviors serves as an excellent indicator of the types of events that place one at risk for gunshot victimization. Like needle sharing or unprotected sex in the spread of HIV (Klovdahl et al., 1994; Pivnick et al., 1994), co-offending exposes an individual to situations, behaviors, and people that might elevate the probability of victimization.

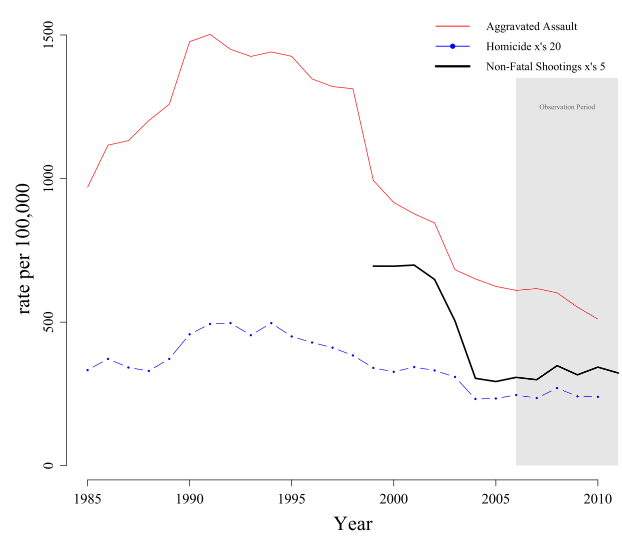


**Fig. 1.** Violent crime rates in Chicago, 1985–2011.
*Source*: Homicide and aggravated assault data are taken from the FBI unified crime report.

## 3. The setting: gun violence in Chicago

Before proceeding to our analysis, it is important to first understand the distribution of our dependent variable in the city of Chicago, as this provides insight into the distribution of an important public health outcome in a major metropolitan area with high rates of both fatal and nonfatal shootings. Prior research in Chicago demonstrates strong racial and spatial inequalities in the distribution of homicides (Morenoff et al., 2001), robberies (Bernasco and Block, 2011), and other violent and property crimes (Block and Block, 1995; Morenoff and Sampson, 1997), but, to the best of our knowledge, no study examines the distribution of nonfatal gunshot injuries. In this section, we briefly describe the overall trend and distribution of nonfatal gunshot injuries in Chicago.

Like most cities in the U.S., Chicago experienced a large decline in violence and gun-related crimes during the late 1990s and early 2000s. As seen in Fig. 1, rates of aggravated assaults, homicide, and nonfatal shootings in Chicago have declined precipitously since the mid-1990s. In Fig. 1, nonfatal shootings are classified using the arrest data in which an individual was charged with injuring an individual with a firearm. All other estimates in this article are based on the victimization records described above. Assaults decreased from a peak of 1502.3 per 100,000 in 1991 to 510.4 in 2010. Likewise, rates of homicide decreased 50 percent from a high of 33.1 per 100,000 in 1994 to 16.0 in 2010. Although we lack data on nonfatal shootings for the entire period, our data suggest that nonfatal shootings display a similar trend, decreasing by 55 percent from a rate of 139.7 per 100,000 in 2001 to 63.3 in 2010.

This decline notwithstanding, rates of homicide, assault, and gun violence remain stubbornly high in Chicago, well above the national averages. In 2010, the homicide rate in Chicago was 16.0 per 100,000, four times higher than the national rate of 4.8 and two times higher than other large cities like Los Angeles (6.6 per 100,000) and New York City (6.4 per 100,000) (FBI, 2011). Likewise Chicago's rate of aggravated assault was almost twice the national rate: 510.5 per 100,000, as compared to the national average of 252.3 and rates in other large cities like Los Angeles (246.3) and New York (334.4).

### 3.1. Race specific rates

As described above, rates of gun violence differ drastically by race and ethnicity. The same is true of gunshot injuries in Chicago during our study period. Fig. 2 graphically displays the average annual rate of nonfatal gunshot victimization (per 100,000) from our victimization data in Chicago from 2006 to 2012 by race, gender, and age group. Throughout this paper we use the term black to refer to non-Hispanic blacks, white to refer to non-Hispanic whites, and Hispanic to refer to white Hispanics.

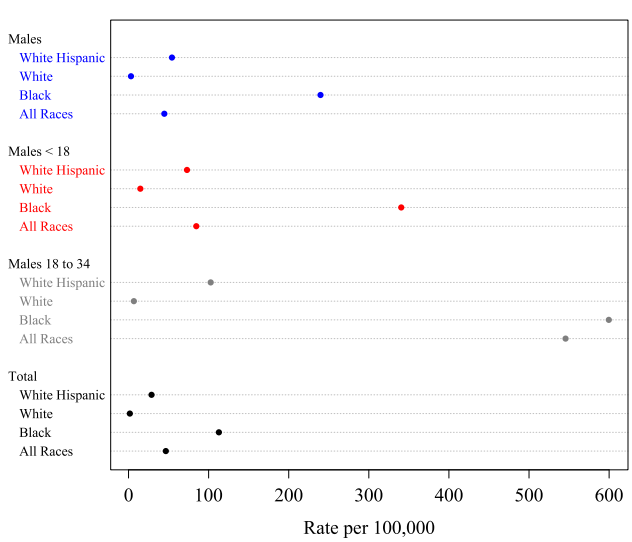


**Fig. 2.** Rates of nonfatal gunshot victimization in Chicago, 2006–2012.

Overall, the average nonfatal gunshot victimization rate in Chicago is 46.5. This rate is considerably lower for Whites (1.62) and Hispanics (28.72), but more than double for Blacks (112.83). Such disparities only widen when considering gender and age. The rate for all males is 44.68 per 100,000, while for Black males is 239.77. This rate increases nearly 30 percent for Black males under 18 years old, and the rate for Black males between 18 and 34 is a staggering 599.65 per 100,000—twelve-times the city average and indicating that roughly 1 in 200 men in this group are victims of a nonfatal shooting each year.

### 3.2. Place specific rates

The uneven distribution of homicides, robberies, and other violence in Chicago neighborhoods is well documented. The same is true of nonfatal gunshot injuries in our study. Fig. 3 displays the number of nonfatal gunshot victims analyzed in our data across 282 police beats in Chicago (Chicago Police Department, 2011).

Fig. 3 shows the spatial clustering of gun violence, with the highest incidence on the west and south sides of the city—historically black and high-crime areas of the city (Sampson, 2012). The average number of gunshot victims per beat is 36.4. However, this distribution is highly skewed. Twenty percent of all beats have either none or a single non-fatal shooting event during the observation period, while 6 percent of all beats account for 25 percent of all gunshot victims.

The population and spatial distributions of non-fatal gunshot injuries in our study display patterns consistent with prior research on gun homicide: young minority males are at the greatest risk of victimization and nonfatal shootings cluster in a small number of geographic locations. However, most individuals with these risk factors or living in high gun violence areas never become a victim of gunshot injuries. We maintain that rates of gunshot victimization will vary by one's position in risky social networks, the contours of such networks, and the levels of exposure to gunshot victimization in one's network.

## 4. Gun violence in co-offending networks

As described above, we created co-offending networks for the entire city of Chicago. These networks were derived from all arrests between January 2006 and September 2012. The resulting networks contain 169,725 unique individuals who have a co-offending tie to at least one other person arrested during this period. Isolates—individuals without a co-offending tie to another person—are excluded in the present analysis. This network represents approximately 6 percent of the total population of Chicago and 40 percent of all individuals arrested during this period. Individuals in these networks are overwhelming young (average age of 25.7 years), male (78.6 percent), and black (69.5 percent). Approximately 39 percent of the sample is identified by the police as members of a street gang. Descriptive statistics are presented in the Appendix (Table A1).

In total, we identified 25,339 connected components in the total network—i.e., subgraphs of the network in which any two vertices are connected to each other by paths and which are connected to no other vertices in the network (Wasserman and Faust, 1994); components range in size from two individuals to 107,740 individuals. Like many networks, this population is dominated by a single large component containing 63 percent of all individuals. In

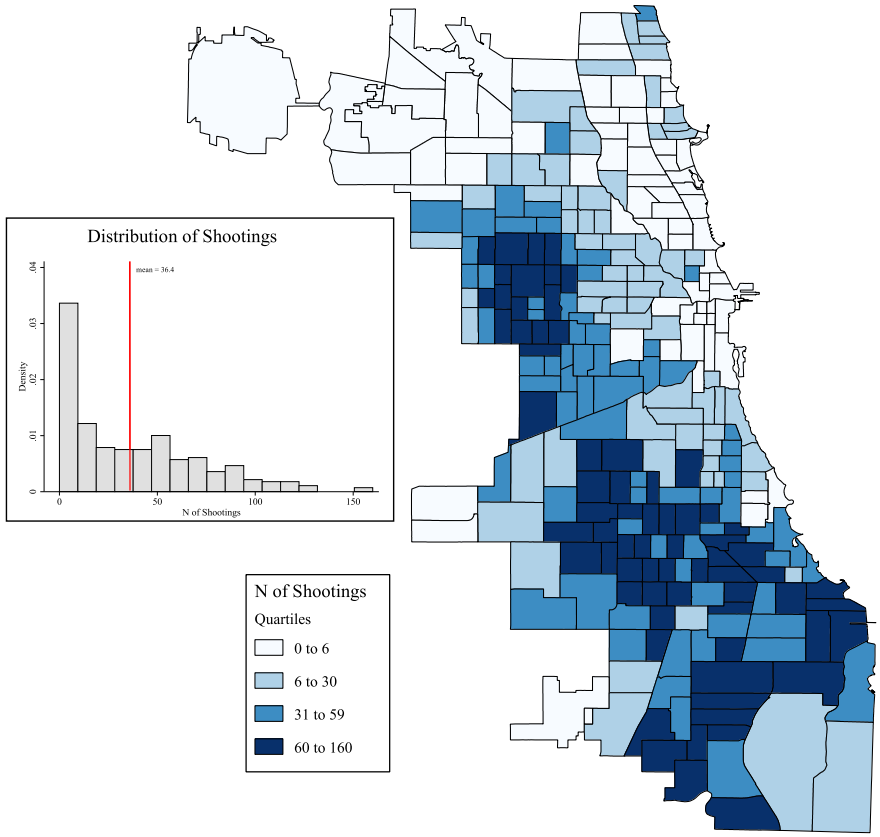


**Fig. 3.** Number of nonfatal gunshot victims in Chicago by police beat, 2006–2012.

other words, nearly two-thirds of all offenders in Chicago are connected to each other directly or indirectly. Also like many other networks, the distribution of ties in the co-offending network is highly skewed (Appendix Fig. A1). On average, individuals have 4 ties to other individuals in the network. But, the majority of individuals (57 percent) are tied to either 1 or 2 other people.

Consistent with our argument, the majority of all non-fatal gunshot injuries in Chicago occur in this network: victims in 7527 shootings during this time period—approximately 70 percent of all shootings—can be identified in these co-offending networks. Not surprisingly, the majority of those shootings—89 percent—occur in the largest component. This concentration of non-fatal shootings suggests an even higher concentration of non-fatal shootings than gun homicides, as only 46 percent of all the gun homicides occur in these networks.

This finding has (at least) two implications for our understanding of non-fatal gunshot injuries. First, the concentration of non-fatal gunshot injuries in networks such as these demonstrate that such incidents are more concentrated than previously thought, and even more concentrated than gun homicide by either demographic group or place. Our findings indicate that *70 percent of all non-fatal shootings occur in networks comprising less than 6 percent of Chicago's total population*. This distribution of shootings within co-offending networks fundamentally changes how we assess the distribution of risk in Chicago.

To illustrate this point, Fig. 4 demonstrates this change in risk assessment by showing the differential rates by arrest status and presence in a co-offending network. The average annual city rate during this period is 62.14 per 100,000. The rate is five times higher for individuals who were arrested during this time period but who were not in a co-offending network. And the rate is an astonishing 740.48 per 100,000 for individuals who were arrested and who also are located in one of the co-offending networks—a rate more than twelve times higher than the city rate and more than two times higher than individuals who were arrested but not in a co-offending network.

Second, this concentration of gunshot injuries in co-offending networks suggests a tight link between the distribution of co-offending networks and the distribution of nonfatal violence. Each of the victims in these networks was arrested at least once in the 5-year period around their victimization. If arrests represent at least some form of participation in risky behaviors, then it is safe to assume that the majority of gunshot victims are actively engaged in or exposed to situations, people, and behaviors in these networks that are conducive to gun use and violence. Having established the concentration of gunshot victims in networks such as these, our

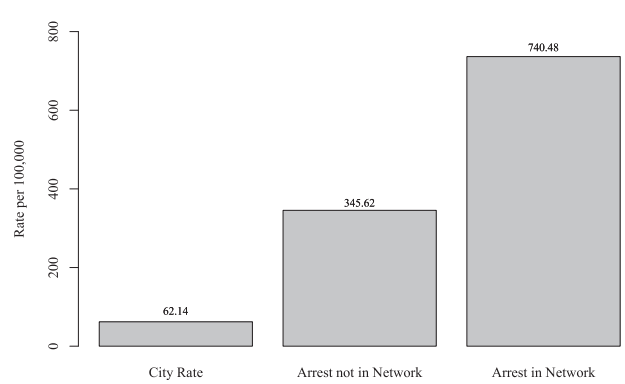


**Fig. 4.** Rates of nonfatal gunshot victims by arrest and network membership status, 2006–2012.

second objective is to investigate one possible mechanism responsible for such clustering: exposure to gunshot victims in one's network.

## 5. The social contagion of gunshot victimization

One of the hallmarks of social network analysis is the study of *peer influence*, the extent to which people change their behavior, attitudes, and opinions to be compatible with friends and associates (for a review, see Kadushin, 2012; Marsden and Friedkin, 1993). Often, such influence gets cast under the broader notion of *contagion* in which a particular idea, technology, belief, disease, etc. diffuses within a population. In epidemiological terms, new cases of a particular disease are caught as the pathogen is transmitted from one person to the next. The idea of *social contagion* refers specifically to mechanisms by which diffusion occurs in a population, such as imitation, competition, and communication (Burt, 1987; Kadushin, 2012).

Evidence suggests that some health behaviors—including risky health behaviors such as smoking and substance abuse—are susceptible to peer influence and social contagion processes (Christakis and Fowler, 2008; Fujimoto and Valente, 2012; Haynie, 2001; Mercken et al., 2009). Although the extent to which such processes are causal is a matter of some debate (Aral, 2011; Christakis and Fowler, 2011; Cohen-Cole and Fletcher, 2008), there is general agreement that such behaviors cluster non-randomly within networks. Our aim is not to make direct causal claims, but rather to determine if the clustering of non-fatal gunshot injuries in our co-offending networks persists when accounting for individual risk factors and neighborhood-level variation.

### 5.1. Measuring exposure to gunshot victims

To assess whether or not social contagion plays a role in the distribution of non-fatal gunshot injuries in the co-offending networks, we run a series of logistic regression models on whether or not an individual is a victim (1 = yes) on individual level risk factors and a term for exposure to victimization in one's social network. More specifically, we employ a series of "affiliation exposure" models developed by Fujimoto and colleagues (Fujimoto et al., 2012). These models capture social influence by measuring joint participation or co-membership in two-mode affiliation data. Traditional network effects models capture social influence and the interdependence among observations by modeling individual-level effects, as well as network-level effects by specifying an appropriate weight matrix, $W$, defined on a single mode network (Leenders, 2002). For example, several studies employ network effects models to demonstrate the relationship between one's own substance abuse and exposure to one's peers' substance abuse (e.g. Fujimoto and Valente, 2012). Affiliation exposure models extend this logic by operationalizing the weight matrix, $W$, using the off-diagonal values of a one-mode co-membership matrix converted from two-mode affiliation matrix (see, Fujimoto et al., 2012). The diagonal of the co-membership matrix represents the number of events (arrests) for each individual, which we remove in the weight matrix so that it represents the network ties between individuals without information about each individual's behavior (Fujimoto et al., 2012). Our modeling approach, like the affiliation network exposure model, relies on a one-mode binary projection of a two-mode matrix—in this study, a co-offending network of individuals who were arrested together.

Our use of affiliation exposure models provides an important extension of these models by applying them to behavioral data. As described above, prior applications of affiliation exposure models have relied almost exclusively on joint membership or joint participation, such as members of the same sports team or students in the same classroom. In contrast, the co-offending networks represent actual *behaviors* and, in most cases, these behaviors are dyadic.

Here, we define *network exposure* as the extent to which an individual is connected to gunshot victims in their network. In non-technical terms, we seek to measure the percentage of one's associates who are gunshot victims. Individuals have greater network exposure if their network is saturated with gunshot victims and lesser network exposure if they are not connected to any gunshot victims.

Following Fujimoto and Valente (2012; also Fujimoto et al., 2012), we measure network exposure to violence by multiplying the one-mode binary co-offending matrix (a symmetric adjacency matrix indicating which individuals are co-offenders) and a vector indicating whether each person in the co-offending network is a victim. The resulting vector is then divided by a vector indicating the total number of people each individual is connected to, which row normalizes the exposure term. Formally, exposure is measured:

$$E_i = \frac{\sum_{j=1} W_{ij} Y_j}{\sum_{j=1} W_{ij}} \quad \text{for } i,j = 1,\ldots,N \quad i \neq j$$

where $W_{ij}$ is the adjacency matrix of co-offenders, with $W_{ij} = 1$ if ego ($i$) and alter ($j$) are co-offenders, and $Y_j$ is the vector of alters' ($j$) victim status, with $Y_j = 1$ if alter ($j$) is a gunshot victim. The result, ego's network exposure to victims ($E_i$), is the percent of $i$'s immediate network who are victims.

The row-normalized exposure terms lack information about the number of people each person is connected to in the network, retaining only the percent of those connections that are victims. As we describe further below, we account for this in the models by including individuals' degree (the number of unique alters to which one is tied *via* co-arrest) as a control (see, Fujimoto and Valente, 2012).

Positive and statistically significant network exposure terms in the regression models indicate that an individual's probability of victimization is related to the victimization of his/her associates when controlling for individual factors and other model parameters. In other words, these results would suggest that an individual who is highly connected to gunshot victims is also likely to be a victim him/herself.

### 5.2. Indirect exposure to gunshot violence

People's local social networks are embedded in larger social structures. Indeed, it is precisely these local networks that build upon and nest within each other to create the larger social networks (Watts and Strogatz, 1998). Although individuals may not be aware of these networks, such social structures can have a profound effect on them (see, Bearman et al., 2004). In sexual networks, for example, an individual may not be aware of her current partner's past sexual partner or her partner's past partner's partner, but whether or not these more distal individuals had an STD has consequences for disease contraction. Similar distal effects of network exposure have also been found on patterns of delinquency (Payne and Cornwell, 2007) and smoking and substance abuse (Fujimoto and Valente, 2012).

To measure the distal effects of exposure, we calculate individuals' network exposure to violence not only though their immediate ties, but also through their indirect second degree (i.e. friends of friends) and higher-order ties. To this end, we begin with

the adjacency matrix of co-offenders' direct ties, and increase the range of indirect ties up to a distance of four by exponentiating the adjacency matrix. The number of times the adjacency matrix is exponentiated corresponds to the shortest path, or geodesic distance between ego and alters—i.e., $W_{ij}^2$ represents all ties with a geodesic distance of two, $W_{ij}^3$ represents all ties with a geodesic distance of three, and so on (Wasserman and Faust, 1994).

We sum the exponentiated matrices for nested distances to generate an inclusive measure, which represents all of the alters that ego is connected to within a particular distance (Fujimoto and Valente, 2012). The cell values of inclusive matrices represent the total number of ties connecting two individuals. We remove the diagonal of the inclusive matrices, so that the sum of ego's ties with him or herself is zero. We also conducted analyses using binary inclusive matrices for all distances, which yielded nearly identical results (available upon request). For example, the inclusive measure for ties within a geodesic distance of three paths is the sum of ego's tie to alter (first degree), everyone ego is connected to through alter (second degree), and everyone ego is connected to through all of the alter's alters (third degree). The network exposure of ego to all victims within a geodesic distance of three paths would then be measured as:

$$E_i = \frac{\sum_{j=1}\left(W_{ij} + W_{ij}^2 + W_{ij}^3\right)Y_j}{\sum_{j=1}\left(W_{ij} + W_{ij}^2 + W_{ij}^3\right)} \quad \text{for } i,j = 1,\ldots,N \quad i \neq j$$

The resulting network exposure vector represents the percent of each persons' ties within a given path distance who are victims. Table 1 lists the mean levels of exposure at each distance used in our analyses.

The mean first-degree exposure to non-fatal gunshot victims is 0.063, indicating that approximately 6 percent of a person's associates are gunshot victims. However, the range of exposure is quite large, ranging from zero (none of one's associates are victims) to 1 (all of one's associates are victims). As the distance of ties increases to include more direct and indirect paths in the network, so too does the mean level of exposure. For instance, within a geodesic distance of two paths, the mean exposure is 0.065. This means that among first- and second-degree ties, 6.5 percent of the average person's associates have been gunshot victims. Because these measures are inclusive, exposure terms are highly correlated with each previous level (see, Appendix Table A2).

The proportion of people who have no network exposure to a victim decreases as geodesic distance increases, but this decrease varies significantly by race (see Fig. 5). White co-offenders have the least exposure to victims across all geodesic distances, with 70.6 percent maintaining zero exposure within a geodesic distance of four paths. Roughly the same proportion of Black and Hispanic co-offenders have no exposure to victims in their immediate network (77.1 and 79.9 percent, respectively). However, the decrease in this proportion is steeper among those who are Black, with only 31.5 percent maintaining zero exposure within geodesic distance of four, compared to 46.1 percent of those who are Hispanic. Put another way, by a distance of four, more than 50 percent of direct and indirect associates of Black and Hispanic individuals in the network contain at least one shooting victim.

**Table 1**
Descriptive statistics of network exposure terms.

| | Mean (SD; min, max) |
|---|---|
| Network exposure[a] | |
| Distance 1 | 0.063 (0.167; 0, 1) |
| Distances ≤ 2 | 0.065 (0.110; 0, 1) |
| Distances ≤ 3 | 0.069 (0.100; 0, 1) |
| Distances ≤ 4 | 0.074 (0.095; 0, 1) |

$N = 169{,}620$.
[a] The mean number of victims a person in the network is exposed to within a given path distance.

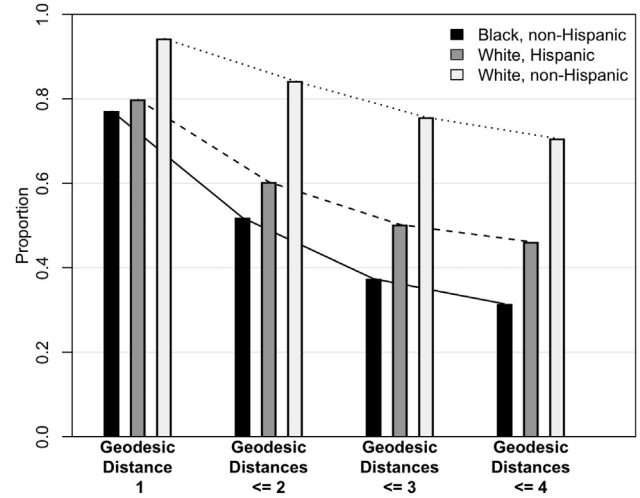


**Fig. 5.** Proportion with no network exposure to gunshot victims by geodesic distance and race group.

## 6. Results

To test the extent to which individual victimization is related to network exposure, Table 2 presents results from a series of logistic regression models, each with a term for network exposure. In addition to the exposure terms, all of the models include covariates for individual risk factors including: sex (1 = female, 0 = male), police identified gang membership (1 = yes, 0 = no), age (in years), and a series of dummy variables for race (White, Hispanic, Asian/Pacific Islander, Native American, and multi-racial, all as compared to Black). We also include two variables related to the network: a binary indicator of whether or not each person is a member of the largest network component (1 = yes, 0 = no) and a measure for the number of network ties for each person in the network. For our models, the number of network ties for each person is captured simply as the degree (number of unique co-offenders to which one is immediately connected) (Fujimoto and Valente, 2012).

The top of Table 2 lists the estimates from our baseline model with all of the covariates and exposure at a geodesic distance of 1. The bottom half of Table 2 lists the exposure terms from separate models, controlling for all of the covariates listed in the top half of the table. We suppress the covariate estimates for subsequent models in the table since no discernable changes were detected in direction, magnitude, or statistical significance.

As expected, the odds of being a nonfatal gunshot victim in the network are lower for women (OR = 0.264) and decrease with age (OR = 0.962). The odds are also lower for Hispanics (OR = 0.697), Whites (OR = 0.256), and Asian/Pacific Islanders (OR = 0.353) as compared to Blacks. Being a gang member also has a large and statistically significant effect on the odds of victimization: gang members are three times more likely to be victims than similar co-offenders not identified by the police as gang members (OR = 3.299). The network covariates are also associated with an increased probability of victimization. Being a member of the largest network component is associated with a 55 percent increase in the odds of being shot (OR = 1.547). And, each additional co-offender one is directly connected to (degree) is associated with a

**Table 2**
Logistic regression of individual victimization on individual level covariates and network exposure terms.

| | Odds ratio | Std. error | Pr (>\|z\|) |
|---|---|---|---|
| (Intercept) | 0.038 | 0.058 | 0.000 |
| Sex (1 = Female) | 0.264 | 0.069 | 0.000 |
| Race/ethnicity (ref = Black non-Hispanic) | | | |
| White Hispanic (1 = yes) | 0.697 | 0.032 | 0.000 |
| White non-Hispanic (1 = yes) | 0.256 | 0.098 | 0.000 |
| Asian Pacific Islander (1 = yes) | 0.353 | 0.294 | 0.000 |
| Multi-racial (1 = yes) | 0.738 | 0.168 | 0.071 |
| Race unknown (1 = yes) | 0.493 | 0.508 | 0.164 |
| Native American (1 = yes) | 0.748 | 0.599 | 0.629 |
| Gang member (1 = yes) | 3.299 | 0.032 | 0.000 |
| Age (in years) | 0.962 | 0.002 | 0.000 |
| Member of largest component (1 = yes) | 1.547 | 0.041 | 0.000 |
| Degree | 1.033 | 0.001 | 0.000 |
| **The network exposure terms were included in separate models with the covariates listed above.** | | | |

| | Odds ratio | Std. error | Pr (>\|z\|) | AIC (of the models) |
|---|---|---|---|---|
| Baseline model | n/a | n/a | n/a | 52829 |
| Network exposure | | | | |
| Distance 1 | 3.131 | 0.057 | 0.000 | 52482 |
| Distances ≤ 2 | 10.881 | 0.090 | 0.000 | 52248 |
| Distances ≤ 3 | 14.680 | 0.097 | 0.000 | 52219 |
| Distances ≤ 4 | 16.198 | 0.103 | 0.000 | 52267 |

$N = 169{,}620$.

3 percent increase in the odds of victimization (OR = 1.033). These findings hold for all subsequent models.

In support of our main hypothesis, the coefficients for the network exposure terms in Table 2 provide evidence that individual gunshot victimization is correlated with exposure to violence in one's social network. Indeed, the network exposure terms are positive and significant for all models up to a geodesic distance of 4. The exposure term at a distance of 1 indicates that the odds of being shot increase by 1.1 percent for each additional percent of one's associates who are victims. If 10 percent of one's associates are victims, the odds of being shot increase by 12.1 percent, compared to someone with no associates who are victims; and if half of one's associates are victims, the odds of being shot would increase by 76.9 percent. The majority of individuals in the network have one or two immediate associates, and their exposure would increase from zero to 50 percent (or more) if just one of their associates is a victim. Thus, even small increases in exposure to victimization in one's immediate network are associated with large increases in the likelihood of victimization.

The direction and significance of the exposure terms at distances >1 also indicates that the effects of exposure on individual victimization extend beyond one's immediate social circle. Put another way, parameter estimates for the higher order exposure terms suggest that indirect exposure to gunshot victims contributes to one's own victimization. The magnitude of this association increases the further one moves outward in their social network because the network ties are additive—namely, distances ≤ 2 includes one's associates and one's associates' associates and so on. At distances ≤ 2, the odds of victimization increase by 2.4 percent for every 1 percent increase in exposure. At 10 percent exposure at distances ≤ 2 (i.e., 10 percent of your direct and indirect associates are victims), one's odds of victimization increase by 27.0 percent, compared to someone with no exposure to victims. Increases in the odds of victimization at 10 percent exposure continue to grow at distances ≤ 3 (30.8 percent) and distances ≤ 4 (32.1 percent), although overall model fit indicated by the AIC does not improve beyond distances ≤ 3.

Two additional dimensions regarding the association of exposure and victimization also arise from these results: (1) even small levels of exposure have a dramatic effect on the odds of victimization, and (2) the effects of exposure vary significantly by race. To illustrate these relationships, Fig. 6 plots the predicted probability of being a victim by levels of network exposure when degree is held constant at its mode and all individuals are members of the largest component for all men in the sample ages 14 to 24. In this figure, we also include predicted probabilities for Blacks, Whites, and Hispanics, and differentiate between gang members and non-gang members in order to present as wide a range of predictions as possible. The first row presents the estimates at an exposure distance of 1, the second row presents the same estimates at exposure distances ≤ 2, the third row presents the same estimates at exposure distances ≤ 3, and the fourth row presents the estimates at an exposure distances ≤ 4.

The first column of Fig. 6 plots the mean predicted probability of being a victim by the level of exposure to gunshot victims for young men of all races. For one's immediate social network (distance = 1), the mean probability of victimization for these young men is 0.041 at the 10 percent exposure level and 0.062 at the 50 percent exposure level. Furthermore, the predicted probability of victimization increases with distance from victims. For example, at distances ≤ 2 (friends and friends' friends) 50 percent exposure yields a 0.096 predicted probability of victimization. As seen in both Fig. 6 and Table 2, the increased effects of distance on exposure are greatest when moving from a distance 1 to distances ≤ 2.

Moving across the rows of Fig. 6 demonstrate that the differential exposure to gunshot victims by race influences the predicted probability of victimization. In short, Fig. 6 shows that the predicted probabilities are highest for black men at all exposure levels and network distances, compared to the other race groups, and for gang members of all races, compared to those not in gangs. This extends prior research on the risks of gang membership by suggesting that part of this risk is attributable to an increase in exposure to victims within gang members' networks. If gangs are first and foremost social networks, these findings may imply that the structure of gang networks have a particularly salient impact on rates of victimization that warrant additional research (Papachristos, 2006). This figure clearly shows that the probability of being a victim is highest for black gang members, with Hispanic gang members following closely, but significantly behind them. For example, the predicted probability of victimization for an 18 year old, black, gang member with 1 percent exposure at distance 1 is 0.091, and increases to 0.150 at 50 percent exposure. When including associates' associates at distances ≤ 2, the probability of victimization at 50 percent exposure increases to 0.219. The comparable predicted probability of being shot for Hispanic men in gangs with 50 percent exposure is 0.109 at distance 1, increasing to 0.165 at a distances ≤ 2.

However, there is overlap among black men and Hispanic men who are not gang members, and white gang members. Even after controlling for exposure to victims, being white appears to mitigate the increased probability of victimization associated with being a gang member, putting these men in (relative) parity with men not in gangs for the other two race groups. White men not in gangs fare the best among these six sub-groups, with the lowest predicted probability of being a victim.

### 6.1. Robustness check

As a robustness check on our results, Table 3 presents a set of results from logistic regression models that control for unobserved neighborhood-level variation, with "neighborhoods" defined as police beats (see, Appendix Table A3). Following Gelman and Hill

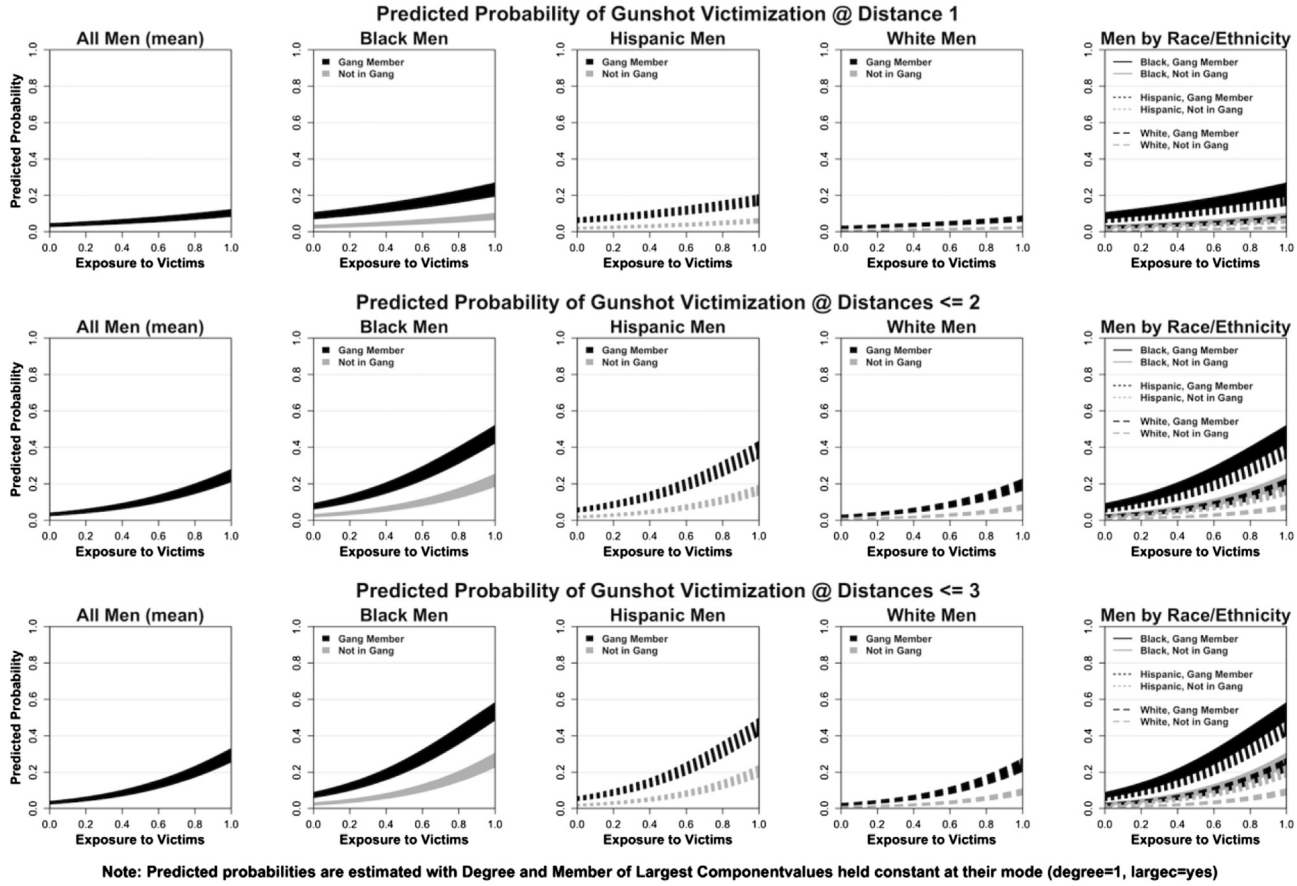


**Fig. 6.** Predicted probability of gunshot victimization for 14–24 year old males by gang membership, race/ethnicity, and network exposure at geodesic distances 1–3.

(2007), we use varying-intercept models to control for this neighborhood-level variation, without having to estimate coefficients for each of the 282 police beats. Given the importance of space in the distribution of crime, these models test the extent to which our results are sensitive to variation in unobserved neighborhood characteristics. While results for the varying-intercept models in Table 3 are not directly comparable to the results in Table 2 due to missing neighborhood data, the parameter estimates for covariates are very similar. Results in Table 3 show that our findings are indeed robust to variation in unobserved characteristics of police beats. For example, the exposure term for Distance = 1 in the varying-intercept model (OR = 2.958) is quite similar to the effect without neighborhood controls (OR = 3.256). The same is true of the other exposure terms.

## 7. Discussion

This study had two objectives: to analyze the distribution of nonfatal gunshot injuries across high-risk networks and to explore whether victimization in these networks is related to social contagion. With regards to the first objective, our findings suggest that nonfatal gunshot injuries are far more concentrated than previously thought. *Seventy percent of all nonfatal gunshot injuries during a six-year period occurred in co-offending networks containing less than 6 percent of the city's population*. Furthermore, 89 percent of those victims were contained in a *single* social network of 107,740 unique individuals. Such concentration considerably nuances estimates of gunshot victimization. While the overall rate of gunshot victimization in Chicago is 62.1 per 100,000, the rate is 740.5 for individuals in a co-offending network, more than twelve times higher than the overall city rate (Fig. 4).

With regard to our second objective, regression results suggest that the probability of victimization is strongly associated with network exposure to nonfatal gunshot victims. That is, the greater the extent to which one's social network is saturated with gunshot victims, the higher one's probability of also being a victim. For individuals with two or fewer immediate associates, the majority of

**Table 3**
Logistic regression models with varying intercepts for neighborhoods.

| | Odds ratio | Std. error | Pr (>\|z\|) | AIC (of the models) |
|---|---|---|---|---|
| **A. Varying-intercept models including the covariates listed in Table 2.** | | | | |
| Baseline model | n/a | n/a | n/a | 45903 |
| Network exposure | | | | |
| Distance 1 | 2.958 | 0.062 | 0.000 | 45635 |
| Distances ≤ 2 | 9.516 | 0.098 | 0.000 | 45470 |
| Distances ≤ 3 | 12.356 | 0.106 | 0.000 | 45464 |
| Distances ≤ 4 | 13.278 | 0.114 | 0.000 | 45512 |
| **B. Comparable models, but without varying intercepts for neighborhoods** | | | | |
| Baseline model | n/a | n/a | n/a | 46091 |
| Network exposure | | | | |
| Distance 1 | 3.256 | 0.060 | 0.000 | 45763 |
| Distances ≤ 2 | 11.303 | 0.095 | 0.000 | 45555 |
| Distances ≤ 3 | 14.870 | 0.103 | 0.000 | 45541 |
| Distances ≤ 4 | 16.259 | 0.110 | 0.000 | 45588 |

$N = 138{,}351$.
*Note*: Results for the varying-intercept models are not directly comparable to the previous set of models, because the varying-intercept models use a smaller number of cases due to missing neighborhood data. The results provided here are for models using the same cases for comparability. The parameter estimates for covariates are very similar regardless of the number of cases used. Full results given in Appendix Table A3.

individuals in the network, their likelihood of victimization is 2–3 times greater if one of their associates is a victim than if they have no exposure to victims. More precisely, our estimates suggest that even small increases in exposure correlate with increases in victimization. For example, every 1 percent increase in exposure to victims in one's immediate social network increases the odds of victimization by 1.1 percent, and a 10 percent increase in exposure to victims in one's immediate social network increases the odds of victimization by 12.1 percent. Such effects, as the predicted probabilities in Fig. 6 show, are larger for blacks and Hispanics and gang members.

Indirect associations also contribute to victimization, meaning that not only one's criminal associates but also the associates of one's criminal associates shape one's risk of gunshot victimization. For instance, 10 percent exposure to victims at distances $\leq 2$ increases the odds of gunshot victimization by 27.0 percent, and 25 percent exposure to victims increases the odds by 81.6 percent. The effect of exposure continues to increase for larger distances, as does individuals' exposure to victims, resulting in large increases in the odds of victimization. At the mean exposure for each distance, the odds of victimization increase by 7.5 percent at distance 1, by 16.8 percent at distances $\leq 2$, by 20.5 percent for distances $\leq 3$, and by 22.8 percent at distances $\leq 4$, compared to a person with no exposure to victims at each distance.

These effects of network exposure vary significantly by race/ethnicity and gang membership. Black gang members have by far the highest probability of victimization across all levels of exposure; they also experience the greatest exposure to gunshot victims in their networks and, as such, are the most susceptible to contagion of violence. Hispanic gang members have the second highest rates, followed by Black non-gang members, Hispanic non-gang members, and White gang and non-gang members (Fig. 6). Such racial differences are of particular note since prior network studies on violence have focused on racially and ethnically homogeneous samples (Papachristos et al., 2012a; Papachristos and Wildeman, 2014).

To be clear, the results from the second stage of our analysis are intended to be merely associational, as we do not purport to provide a causal test. However, we believe our results present provocative evidence of a plausible causal relationship between gunshot violence and network exposure for several reasons. First, our results are robust when controlling for individual level risk factors that have been found to predict victimization in both cohort and cross-sectional studies. Second, our effects persist even under the stringent conditions of neighborhood-level effects. Finally, and given these two conditions, our sample contains the vast majority of the population of gunshot victims in Chicago during this time period. In short, while we cannot make strong causal claims, our analyses go a long way toward controlling for dimensions of homophily (and population heterogeneity) that are available in the data. Future research—especially into causal processes—would do well to consider these issues.

Several limitations are worth noting. First, our data were collected solely by the police. As most crimes go unreported and police exert distraction in those reported events which lead to an arrest, our estimates of the real networks underlying these behaviors are quite conservative. Second, our network ties represent specific behaviors and exclude other types of behaviors that might be conducive to or protective against gunshot injury; future research would do well to consider additional types of network ties including friendship, romantic, familial, classmates, co-workers, and even residential relationships. Third, our decision to dichotomize our co-offending matrix may also undervalue strong ties—in this case individuals who repeated engage in risky behaviors together over an extended period of time. As such, we may be underestimating the effects of such strong ties. Finally, this study aggregated arrest records over a period of time in large part because of the already conservative nature of arrest relationships. However, prior research using networks aggregated over shorter time frames and differential temporal ordering of network ties and outcomes produce co-offending networks with remarkably similar properties as the networks examined here (e.g., degree distributions, density, and clustering) (Papachristos et al., 2012a; Papachristos and Wildeman, 2014). Nonetheless, our decision to aggregate our arrest data might have influenced our results.

These results have considerable implications for our understanding of gun violence reduction and prevention strategies, especially if any of the association uncovered here is due to a causal relationship. First and foremost, these findings present evidence that gun violence spreads through processes of social contagion that are concentrated in risky networks and are associated with specific behaviors, in this case co-offending. Although community-level interventions are necessary for long-term violence reduction, these findings suggest that techniques such as social network analysis may improve violence reduction strategies. In part, techniques for graphing social networks and identifying clusters might be used to identify particularly risky locations within the network for public health interventions. An approach such as this would argue *against* sweeping policies and practices based purely on categorical distinctions such as race and ethnicity and, instead, opt for interventions and policies that consider the observable risky behavior of individuals. Such techniques may not only provide more useful points for intervention, but may also prove to be a more efficacious use of limited resources. Doing so reminds policy makers and practitioners that gun violence, while tragic, is not random.

## Acknowledgments

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## Appendix

**Table A1**
Descriptive statistics for individual level variables and network terms.

| | Percentage or mean (SD; min, max) |
|---|---|
| Victim | 4.4% |
| Age (in years) | 25.701 (11.506; 6, 87) |
| Male | 78.6% |
| Race/ethnicity | |
| Black non-Hispanic | 69.5% |
| White Hispanic | 19.5% |
| White non-Hispanic | 9.4% |
| Asian Pacific Islander | 0.7% |
| Multi-racial | 0.6% |
| Race unknown | 0.2% |
| Native American | 0.1% |
| Gang member (1 = yes) | 38.9% |
| Member of largest component (1 = yes) | 63.5% |
| Degree | 4.048 (5.983; 1, 133) |
| Network exposure[a] | |
| Distance 1 | 0.063 (0.167; 0, 1) |

**Table A1** (*continued*)

| | Percentage or mean (SD; min, max) |
|---|---|
| Distances ≤ 2 | 0.065 (0.110; 0, 1) |
| Distances ≤ 3 | 0.069 (0.100; 0, 1) |
| Distances ≤ 4 | 0.074 (0.095; 0, 1) |

$N = 169{,}620$.

[a] The mean number of victims a person in the network is exposed to within a given path distance.

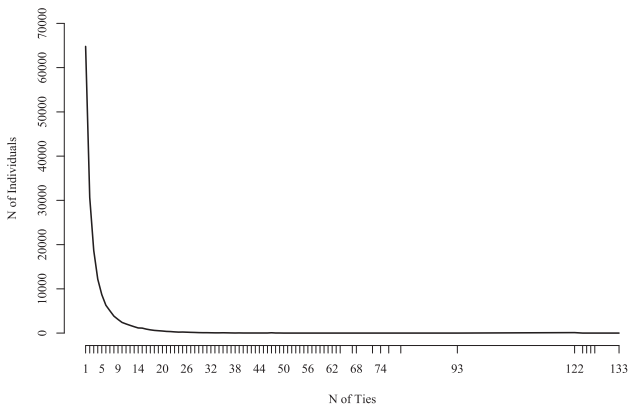


**Fig. A1.** Degree distribution of co-offending network.

**Table A2**
Spearman's rank correlation of network exposure at increasing distances.

| | Distance 1 | Distances ≤ 2 | Distances ≤ 3 | Distances ≤ 4 |
|---|---|---|---|---|
| Distance 1 | 1 | | | |
| Distances ≤ 2 | 0.679 | 1 | | |
| Distances ≤ 3 | 0.644 | 0.892 | 1 | |
| Distances ≤ 4 | 0.566 | 0.854 | 0.961 | 1 |

**Table A3**
Logistic regression models with varying intercepts for neighborhoods.

| | Odds ratio | Std. error | Pr (>\|z\|) |
|---|---|---|---|
| (Intercept) | 0.035 | 0.065 | 0.000 |
| Sex (1 = Female) | 0.259 | 0.073 | 0.000 |
| Race/ethnicity (ref = Black non-Hispanic) | | | |
| White Hispanic (1 = yes) | 0.771 | 0.043 | 0.000 |
| White non-Hispanic (1 = yes) | 0.374 | 0.109 | 0.000 |
| Asian Pacific Islander (1 = yes) | 0.444 | 0.311 | 0.009 |
| Multi-racial (1 = yes) | 0.848 | 0.178 | 0.353 |
| Race unknown (1 = yes) | 0.206 | 1.014 | 0.120 |
| Native American (1 = yes) | 0.698 | 0.739 | 0.626 |
| Gang member (1 = yes) | 3.222 | 0.035 | 0.000 |
| Age (in years) | 0.964 | 0.002 | 0.000 |
| Member of largest component (1 = yes) | 1.472 | 0.044 | 0.000 |
| Degree | 1.035 | 0.001 | 0.000 |
| **The network exposure terms were included in separate models with the covariates listed above.** | | | |

| | Odds ratio | Std. error | Pr (>\|z\|) | AIC (of the models) |
|---|---|---|---|---|
| Baseline model | n/a | n/a | n/a | 45903 |
| Network exposure | | | | |
| Distance 1 | 2.958 | 0.062 | 0.000 | 45635 |
| Distances ≤ 2 | 9.516 | 0.098 | 0.000 | 45470 |
| Distances ≤ 3 | 12.356 | 0.106 | 0.000 | 45464 |
| Distances ≤ 4 | 13.278 | 0.114 | 0.000 | 45512 |
| **Comparable models – same cases, but without varying intercepts for neighborhoods** | | | | |
| Baseline model | n/a | n/a | n/a | 46091 |
| Network exposure | | | | |
| Distance 1 | 3.256 | 0.060 | 0.000 | 45763 |
| Distances ≤ 2 | 11.303 | 0.095 | 0.000 | 45555 |
| Distances ≤ 3 | 14.870 | 0.102 | 0.000 | 45541 |
| Distances ≤ 4 | 16.259 | 0.110 | 0.000 | 45588 |

$N = 138{,}351$.

*Note*: Results for the varying-intercept models are not directly comparable to the previous set of models, because the varying-intercept models use a smaller number of cases due to missing neighborhood data. The results provided here are for models using the same cases for comparability. The parameter estimates for covariates are very similar regardless of the number of cases used.

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