Network spillovers and neighborhood crime: A computational statistics analysis of employment-based networks of neighborhoods*,**

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KEYWORDS: neighborhood crime; network spillovers; econetworks; disadvantage; public control; commuting

*ACKNOWLEDGEMENTS
The authors are thankful for funding from the National Science Foundation (NSF CNS-1544455). Graif is also grateful for funding from the National Institute of Health (NIH K01-HD093863 and for support from the Penn State University's Population Research Institute (NICHD R24-HD041025). Li and Kifer also thank NSF for awards #1652525 and #1054389, respectively.

***NOTE*
This is an Accepted Manuscript of an article accepted for publication by Taylor & Francis in Justice Quarterly on 03.27.2019, Article DOI: 10.1080/07418825.2019.1602160, available at http://wwww.tandfonline.com/10.1080/07418825.2019.1602160

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Abstract

Research on communities and crime has predominantly focused on social conditions within an area or in its immediate proximity. However, a growing body of research shows that people often travel to areas away from home, contributing to connections between places. A few studies highlight the criminological implications of such connections, focusing on important but rare ties like co-offending or gang conflicts. The current study extends this idea by analyzing more common ties based on commuting across Chicago communities. It integrates standard criminological methods with machine learning and computational statistics approaches to investigate the extent to which neighborhood crime depends on the disadvantage of areas connected to it through commuting. The findings suggest that connected communities can influence each other from a distance and that connectivity to less disadvantaged work hubs may decrease local crime—with implications for advancing knowledge on the relational ecology of crime, social isolation, and ecological networks.

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INTRODUCTION

A century old body of research on the role of socioeconomic disadvantage in increasing neighborhood crime has mainly focused on within-neighborhood or geographically proximate social conditions (Peterson & Krivo, 2009, 2010; Sampson, 2012; Shaw & McKay, 1942). However, evidence increasingly suggests that disadvantage outside of a neighborhood or its immediate surroundings is also associated with local crime (Mears & Bhati, 2006; Taylor, 2015). This is not surprising, given that activity space research shows that many people spend a great deal of their day in activities occurring in places outside their home areas (Krivo, Washington, Peterson et al., 2013), forming an "econetwork" - a network of places - which can affect their outcomes and behaviors (Browning, Soller, & Jackson, 2015; Hoeben & Weerman, 2016). The activity space literature mostly focuses on individuals, yet neighborhoods may also be affected by residents' exposures to risks in areas where they go to work, attend school or church, go grocery shopping, or where co-offending or gang conflict occurs (Browning, Calder, Soller, et al., 2017; Matthews & Yang, 2013; Papachristos, 2015; Papachristos, Hureau, and Braga, 2013; Sampson, 2012; Schaefer, 2012; Wikström, Ceccato, Hardie, et al., 2010). Indeed, research on public social control suggests that inflows of external resources such as mortgage loans decrease neighborhood crime (Velez, Lyons, & Boursaw, 2012).

In this study, we draw motivation from insights on econetworks, spatial spillovers, and the relational ecology of neighborhoods and crime (Sampson 2012) to analyze the relevance of ties to external resources and address an important next question: Does exposure to work places of higher disadvantage increase local crime above and beyond the role of local disadvantage? This question has not yet been explored, to our knowledge, due to great challenges in collecting activity data. However, addressing this question is important. First, studies find that neighborhoods are connected to each other based on: co-offending (Schaefer, 2012), gang conflicts (Papachristos et al., 2013), residents changing addresses (Sampson & Sharkey, 2008), and transportation (Boivin & Felson, 2017; Boivin & D'Elia, 2017; Felson & Boivin, 2015; Graif, Lungeanu, & Yetter, 2017; Matthews et al., 2010; Wang et al., 2016). We thus have many indications that neighborhoods are not isolated islands or closed systems, as they have been predominantly assumed to be (Browning & Soller, 2014; Graif, Matthews, &, Gladfelter 2014). Therefore, an important question is to what extent external ties matter for neighborhood crime.

Second, great advances in the communities and crime literature highlight the importance, across multiple large cities, of spatial interdependencies and spatial spillovers -- as proximate geographic areas are powerful forms of extra-local influence (Anselin et al., 2000; Bernasco & Block, 2011; Taylor, 2015). A growing body of work indicates that geographic proximity to neighborhoods of high disadvantage increases local residents' victimization (Graif & Matthews, 2017), involvement in crime (Graif, 2015; Vogel & South, 2016), and the overall crime in a neighborhood (Peterson & Krivo, 2009, 2010). These spatial spillovers (i.e., *extra-local effects*), have been observed across myriad outcomes (e.g., Crowder and South, 2011), yet the underlying spatial links have mostly been assumed rather than modeled explicitly, largely due to data limitations. Specifically, past studies have not considered commuting flows as possible conduits for spatial or network spillovers on crime. Doing so may greatly advance our understanding of population mobility and spatial ties and their significance for crime. The current study gets a step closer to this goal by examining one type of spatial link based on observed commuting flows of residents between home and work areas. Important classic and emerging bodies of work motivate our theoretical expectations that interactions in work areas may relate to within-neighborhood processes that affect crime. Although exposures to areas of work do not always mean significant interactions in such places and our data presents a birds' eye view, this analysis offers a critical first step in motivating further research on underlying mechanisms.

Third, when focusing on disadvantage in a particular neighborhood, programs and policies may be less successful in decreasing crime if we do not pay attention to spillovers from connected areas. If neighborhood crime depends on disadvantage levels in areas connected through social ties, reducing disadvantage in one neighborhood may be insufficient in reducing crime without also reducing disadvantage in socially connected areas. However, if we do pay attention to which neighborhoods are more connected and have stronger ties to other disadvantaged areas, interventions may lead to controlling crime across a wider range of areas.

To understand the complex role of external disadvantage in shaping crime, we focus on neighborhoods in Chicago, a large and diverse city. A great deal of the violence in this city is concentrated in a few historically impoverished and segregated neighborhoods in the South and West side of Chicago (Gorner, 2016a; Wills & Hernandez, 2017).

In sum, the current study explores the connection between crime and commuting patterns among Chicago communities and seeks to contribute to the communities and crime literature by extending the existing research in several ways. First, it addresses an important substantive need in the literature to move beyond the *internal* or *geographically proximate* forces to examine the significance for crime of *ecological network* forces forged through daily mobility of residents between their homes and their jobs. Data accessibility limits our focus to employment-based activity. Nonetheless, this is an important first step in extending the prior focus on residential and nearby areas, as employment-based activity is a daily activity that occupies a great deal of people's time (Lindström, 2008) and work areas may partly overlap with the location of other activities like grocery shopping. Importantly, unlike standard surveys, our data has the advantage of covering the full census of workplaces and workers, over multiple years.

Second, on a methodological level, the current study contributes to the literature by adapting a computational statistics approach in order to account for spatial and network interdependencies. Moreover, it extends prior spatial models by going beyond assumptions of spatial interactions to explicitly model a unique type of spatial mechanism -- daily commuting flows between neighborhoods. Third, the study contributes to the public control literature and to public policy by highlighting that routine connections to less disadvantaged work environments may be key pathways through which neighborhood residents may secure access to outside resources. Finally, this study responds to the need in the activity space literature to extend the predominant focus from individuals to neighborhood implications of residents' routine activities.

FROM INTERNAL EFFECTS TO SPATIAL AND NETWORK SPILLOVERS

Internal neighborhood disadvantage has been traditionally understood as a contributor to local crime because of processes linked to social disorganization, public social control, and routine activities, among others. Socioeconomic disadvantage factors, such as poverty and unemployment, are thought to increase crime as a result of increased economic and social strain of residents and social disorganization processes, such as weakened interactions among residents. Scholars are used to thinking about how internal or spatially proximate disadvantage affect communities. In this study, we extend this focus to examine how a community is affected by disadvantage in its commuting network. This extension is motivated theoretically by classic social disorganization thinking combined with recent insights on routine activities and activity spaces; classic ideas on private and parochial control with ideas on public control.

Internal neighborhood mechanisms

Neighborhood disadvantage weakens a variety of neighborhood processes, which in turn are associated with higher crime. For instance, in an influential review of neighborhood effects studies, Sampson and collaborators (2002) identified four different classes of *internal neighborhood mechanisms* (p. 457-8): a) <u>Social ties / interactions</u>: refer to the quality and frequency of the social relationships and inter-personal exchanges, also defined as social capital (Sampson and Groves, 1989); through bonds and informal pressures, primary ties contribute to "private control" against crime (Hunter, 1985); b) <u>Norms and collective efficacy</u>: refers to shared expectations of social control, informal norms about intervening to benefit children and the community as a whole, which buffer against crime (Sampson et al., 1997); c) <u>Institutional resources</u>: refers to the presence of and participation in organizations and groups in the area that serve the needs of local residents. Participation in organizations protects against crime not just through resources but also through expectations and pressures, or parochial control (Hunter, 1985). Indeed, research shows that organizations and services like youth centers and recreational programs in a neighborhood decrease the odds of aggression in youth (Molnar et al., 2008), rates of institutionally isolated are associated with violence (Thomas and Shihadeh, 2013), and when at-risk youth participate in youth recreation programs, crime rates decrease (Witt and Crompton, 1996); d) <u>Routine activities</u>: refer in part to land use patterns, such as the mix of residential and commercial land use, public transportation nodes, daily inflows of tourists, and customers, which affect the social, physical, and temporal patterns of activity and interactions that people may be exposed to on a daily basis. For instance, research (Haberman and Ratcliffe, 2015) finds that bars and subway stops in a neighborhood as well as in its spatial proximity increase street robberies.

From spatial to network spillovers

Prior work provides evidence that disadvantage effects are not exclusive to residential areas, but also spill over between *geographically proximate* neighborhoods (Peterson and Krivo, 2010). For instance, institutions in surrounding tracts (e.g., recreation centers), have been related to reductions in violence (Peterson, Krivo, and Harris, 2000). Motivated by a growing body of work that documents the existence of spatial spillover patterns (Taylor, 2015), studying the underlying mechanisms of spatial spillovers is a promising area of research (Anselin, 2002; Graif, 2015). Among some of the possible mechanisms of geographic spillovers are factors like residents' daily crossing neighborhood borders for work, which may facilitate the transmission of risks and opportunities between two nearby areas. Spillovers may, then, be observed between distant areas connected through routine commuting. Such social spillovers have been proposed before but, unlike prior research, we measure inter-neighborhood ties rather than assume them based on similarity of residents (Mears & Bhati, 2006). We measure ties based on routine commuting, rather than based on changing homes, co-offending, or other less frequent ties (Papachristos, 2015; Sampson, 2012). Below we discuss examples of how the four classes of neighborhood mechanisms may spill over through routine network ties between neighborhoods.

Social ties and interactions. Social ties and interactions in a neighborhood may matter not only for residents but also for the people who commute to work in that neighborhood from other areas of the city. The quality, quantity, and diversity of friendships in work neighborhoods may compensate for dysfunctional interactions in a home neighborhood. Indeed, studies show that many people have co-workers among their close friends, to whom they talk about important issues (Christakis and Fowler, 2013; Marks, 1994). People also develop at work a wide range of weak ties (infrequent contacts linking otherwise disconnected people), which can be useful for information transmission and norms diffusion (Granovetter, 1973). Indeed, being employed has been associated with larger informal networks (Ziersch, 2005) and social capital gained at work has been shown to impact key individual behaviors, such as quitting smoking (Kouvonen et al., 2008) and a healthier diet (Buller et al., 2000). People also carry *stress* and health risk factors from work to home (House and Smith, 1989; Taylor and Repetti, 1997). For example, Bolger et al. (1989) found that spouses are more likely to have an argument with one another after one had an argument at work. This tension may also affect social interactions with neighbors. Beyond effects on individuals' stress and health, scholars expect that "ties outside of the area will be crucial for understanding local problems" (Hipp and Boessen, 2015, p.290).

Norms and collective efficacy: Collective efficacy dimensions like trust, cohesion, and informal monitoring of children in work areas may show commuters who live in disadvantaged areas of high mistrust what is possible, an alternative view of a safer community more in control of its fate. Exposures at work may provide models of trust or informal control that commuters may then apply at home. Acts like cleaning up litter and vacant lots, installing alarms, fixing lights on street corners, or starting a neighborhood crime watch may help increase local trust and cohesion and reduce crime (Bennett, Holloway, and Farrington, 2006; Crowe, 2000).

Institutional resources: Research on "public control" shows that connections to external institutions and actors like mortgage lenders, police departments, or politicians can decrease local crime as a result of resource flows toward disadvantaged communities (Bursik & Grasmick, 1993; Hunter, 1985). Access to libraries, child care, social and recreational activities, educational or job training programs, and health services in work areas may compensate for institutional isolation at home (Small, 2006; Wilson, 1987). Workers may then influence kin and friends in their home neighborhood to access such resources as well. Beyond their primary functions, organizations connect people to other organizations, widening access to services, information, resources, and new personal ties (Small, 2006; Tran et al., 2013). External institutions and resources have been linked to lower local crime (Peterson, Krivo, & Harris, 2000; Vélez, 2001; Vélez, Lyons, & Boursaw, 2012), likely because they address local economic or social support needs and may protect commuters and families from cynicism or hopelessness, being victimized, or being co-opted into criminal networks at home (Harding, 2010).

Routine activities: The public transportation that connects home and work areas or the mix of residential and commercial land use influence the daily flows of diverse urban travelers, suppliers, and customers, affecting the patterns of social activity and interactions that local residents are exposed to on a daily basis. High risk places in disadvantaged work areas, such as liquor stores, illegal drug markets, and contested basketball courts could at times encourage fights and aggression, forming co-offending ties, or the co-opting of antisocial attitudes, norms, and behaviors that workers may carry into their home neighborhoods. For example, bars in residential and adjacent tracts are related to violent crime in neighborhoods (Peterson, Krivo, & Harris, 2000) and bars and subway stops are related to violent and property crime and disorder offenses, even at a distance (Groff & Lockwood, 2014). Exposure to risky places in a work area may similarly undermine the effects of informal monitoring by primary ties in the home area.

Although the primary focus of this study is not to test such mechanisms, this literature deeply motivates the little explored need to examine the link between local crime and network disadvantage. Our goal is thus to explore the extent to which the link can be observed in practice, and is robust to conservative controls. This is a critical first step, which will, we hope, motivate future research on the detailed mechanisms. Overall, integrating insights from the literature on social disorganization with findings from routine activities and activity spaces, from ideas on private and parochial control with insights on public control, contributes to the expectation that:

Hypothesis 1: The disadvantage of work communities connected to a local community through commuting will be associated with crime in the local community (<u>network disadvantage spillovers</u>).

Possible confounders and related pathways

Several alternative explanations may also explain a link between network disadvantage and crime. First, internally disadvantaged neighborhoods may be connected with similarly disadvantaged work neighborhoods because of stigma or self-reinforcing neighborhood social networks that circulate limited information about jobs and resources, a phenomenon related to selection processes and homophily (Graif et al., 2017; Krivo et al., 2013; Schaefer, 2012). Indeed, audit studies suggest that neighborhood disadvantage affects an individuals' job search, such as receiving a call back after job applications (Bertrand & Mullainathan, 2004; Besbris et al., 2015). Ong (1996) noted that poor residents are limited in finding and keeping a job and in where the jobs they find are located. These insights contribute to the following expectation:

Hypothesis 2: The association between work network disadvantage and local crime may be explained by local disadvantage effects (<u>selective homophily).</u>

Second, if residents of a focal community commute mostly to jobs in the geographic proximity of the focal community, the effect of network disadvantage on crime may be confounded with the spatial spillover effects. Many studies have highlighted the importance of spatial spillovers of disadvantage in increasing local crime (e.g., Peterson & Krivo, 2009, 2010). Graif and Matthews (2017) showed that children's victimization prevalence is increased in poor neighborhoods or in their proximity. This research leads to the following:

Hypothesis 3: The association between network disadvantage and local crime may be explained by spatial proximity to disadvantage and crime (<u>surrounding crime spillovers).</u>

Third, routine activities theory and related situational perspectives on crime suggest that crime is likely if a motivated offender meets a desirable target in a context of weak guardianship

(Cohen & Felson, 1979). This suggests that, as people go work in disadvantaged areas, some may be victimized or exposed to crime. Although rare, commuters may be caught in struggles over status and turf among neighborhood gangs (Harding, 2010; Papachristos et al., 2013). Indeed, work travel patterns are correlated with violent and property crime (Felson and Boivin, 2015; Wang et al., 2016). Moreover, many criminal incidents happen *outside* the victim's or offender's area of residence (Groff & McEwen, 2007; Tita & Griffiths, 2005). Disadvantaged work areas with bars and subway stops may have more disorder and crime (Groff & Lockwood, 2014; Haberman & Ratcliffe, 2015; Peterson et al., 2000). Exposures to crime at work may increase people's fear and stress (Rogers & Kelloway, 1997), which may lead residents to isolate themselves (LeBlanc & Kelloway, 2002), perceive more threats or respond more aggressively to them, affecting neighborhood interactions. Thus, the literature suggests that:

> *Hypothesis 4: The association between the work network disadvantage and local crime may be due to crime spillovers through the network (<u>network crime spillovers</u>).*

DATA AND MEASURES

Data on crime incidents reported to the police, including violent crime and property crime, in Chicago over time was obtained from the Chicago Police Department's Citizen Law Enforcement Analysis and Reporting System under privacy protection through the City of Chicago's Data Portal. Crime data was available only within the city boundaries. Measures of concentrated disadvantage and other compositional and socioeconomic characteristics were based on data from the Decennial Census. Data for 2000 was used to calculate these scores consistently prior to the years in which crime was assessed. The neighborhood boundary data were obtained from the Census TIGER/Line shapefiles and the City of Chicago's Data Portal. Data on commuting flows were obtained from the Longitudinal Employer Household Dynamics (LEHD), a U.S. Census Bureau program that combines Unemployment Insurance reports with administrative, business, and demographic data on business establishments and employees, including the location of businesses and employees' addresses (Abowd et al., 2009).

We aggregated commuting data to the community area level on a yearly basis during the duration of the study (2001-2013). The community areas are our unit of analysis. Prior research recognizes community areas as meaningful, distinct, and reliably measured neighborhood units (Hunter 1974; Sampson 2012 p. 169), which Chicago residents tend to identify with and outsiders easily recognize. Each area has its own name, history, and stable boundary over time. They were originally identified by the University of Chicago and Chicago's Department of Public Health as areas separated by natural barriers such as rivers, parks, and railroads. Unlike census tracts, community areas have remained fairly stable in boundaries and size since the early 1900s (Owens, 2012). These community areas are larger (about 40,000 residents on average) and less homogenous than census tracts. Using community areas instead of tracts avoids situations where workers with jobs in tracts near to where they live would count as commuters. In addition, using community areas helps avoid potential issues related to the confidentiality preserving procedure that Census Bureau applies to the commuting data for smaller areal units.

<u>Dependent variables</u>. The <u>overall crime index</u> is the total count of all recorded crime incidents located in a community area, including violent and property crime. <u>Violent crime</u> is the sum of homicide, sexual assault, battery, robbery, domestic violence, and assault incidents. Each incident is counted once, with the exception of murders, which were counted once per victim. <u>Property crime</u> is the total count of burglary, theft, and motor vehicle theft incidents. Each index is calculated as a function of the number of its specific types of crimes located in a community area each year during the study divided by the population of that community. We estimate crime levels by category and aggregate over three years in order to adjust for random year-to-year

fluctuations and better capture the broad temporal pattern.

In order to address possible concerns regarding the reporting of certain types of violent crime, such as sexual assault and simple assaults (Baumer, 2002; Baumer & Lauritsen, 2010), we also separate robbery and homicide from the violent crime index. Although there may be some differences in the effects by type of crime, the core patterns may be broadly similar across all types. For example, successful strategies to prevent or deal with burglaries or street assaults in a non-disadvantaged area at work may be noted by commuters and subsequently imported to their home community. The same may be said about strategies to prevent or deal with robberies.

Work network disadvantage. The core predictor in our models is the work network disadvantage index. A focal home area's network disadvantage level is a weighted average of disadvantage levels in all work areas connected to it, where each weight is based on the strength of the commuting flow. Network disadvantage is calculated following a similar logic as the surrounding disadvantage index (discussed below). Rather than using spatial weight matrix based on the geographic distance between communities (Anselin, 2002; Anselin et al., 2000), we use a network weight matrix measured separately for each year during the study period. The diagonal of the network matrix is set to null in order to exclude a community's own disadvantage from the calculation of network disadvantage and enable us to examine the role of network disadvantage independent of that of internal disadvantage. The off-diagonal cells are calculated based on the commuting flow between a focal home community and a work community, measured as the sum of outgoing commuters from a focal area to a work area divided by the sum of all outgoing commuters with residence in the home community, regardless of work location, during that year. A focal home area's network disadvantage level is calculated based on the disadvantage level of each of the work communities connected to that focal area weighted by the normalized commuting flow between that work area and the focal area. The flow-weighted disadvantage levels of work communities are then summed across all the work areas connected to the same focal home area. This procedure ensures that the disadvantage levels in work communities that have weaker ties to a home community are given less weight while those with stronger ties (more commuters) are given more weight. To the extent that spatial processes and network processes are conceptually distinct, surrounding areas that are also work hubs may influence a focal area through both pathways. For this reason, the network index includes work destinations that are not, as well as those that are, spatially proximate. Because this strategy can increase concerns about multicollinearity, we ran multicollinearity diagnostics tests and conducted supplementary analyses with network measures that exclude spatially proximate areas.

Sociodemographic controls. To assess the role of work community disadvantage on local crime, independent of selective homophily, we measure the internal concentrated disadvantage. Concentrated disadvantage is a composite scale based on a principal component analysis of the proportion of residents with income under the poverty level, percent with public assistance income, unemployment rate, and proportion of female-headed households with kids. Each item's contribution to the scale is weighted according to its load on the principal component. Other sociodemographic factors that tend to be connected to local crime and may confound the association between network disadvantage and crime are: residential stability, population density, and racial and ethnic composition. Residential stability is a scale based on percent household units occupied by owners and percent residents five years of age and older who had lived in the same house five years. The items are weighted by the factor loads of a principal component analysis. Population density is the number of residents per square feet area. Racial and ethnic diversity is calculated as a Herfindahl index, following prior work (Blau, 1977). Its scores are one minus the sum of squares of the proportions of the population in each of the six racial or ethnic groups: Hispanics, non-Hispanic whites, non-Hispanic Blacks, Asians, Native Americans, and Others. Higher values mean higher diversity.

Geographic spillovers. To assess the role of network disadvantage independently of spatial spillovers, the models control for the levels of *surrounding disadvantage* and *crime*. These are calculated as spatially weighted averages of the disadvantage (or crime, respectively) in the geographic areas surrounding a focal neighborhood. The spatial weight is constructed based on geographic contiguity using the queen criterion (where two areas are considered contiguous if they have any common point on their boundaries). The boundary data are processed in R to calculate the spatial weights. The cells of the spatial matrix are first assigned a value of one if two communities are contiguous and zero otherwise. Next, the values are standardized by row such that they add up to a value of 1. Each cell is next used as the weight of a neighbor's value (of crime or disadvantage) in calculating a spatially weighted average of crime (or disadvantage) in the surrounding areas of a focal neighborhood.

Network and temporal spillovers of crime. Measures of network spillovers of crime are calculated like the network disadvantage measure, but based on work-area crime rather than disadvantage. Including this measure helps us understand the role of network disadvantage independent of the possible role of network crime. In the final models, we also include temporal lag measures of crime aggregated over three years, prior to the dependent variable. This helps us estimate the effect of our core predictors on crime at a given time, independent of prior crime, helping us get closer to understanding differences in crime levels over time.

METHODS

Negative Binomial Regression. To deal with right-skewed count dependent variables and over-dispersion, we start by using a negative binomial regression approach (Osgood, 2000), which uses a gamma prior over the lambda parameter in a Poisson regression. The standard errors are adjusted to account for overdispersion (Boessen & Hipp, 2015; Mears & Bhati, 2006; Osgood, 2000). The dependent variables are crime counts, overall and disaggregated by crime type. The model specification uses population within the unit as an offset (log transformed and the coefficient constrained to one), enabling interpretation of the outcome as a crime rate. The core predictor variable is the network level of concentrated disadvantage. The core controls are internal measures such as residential stability, population density, racial and ethnic heterogeneity, and concentrated disadvantage. Additional controls are: surrounding disadvantage, surrounding crime, network crime, and temporal crime lags. The theoretical motivation and the use of temporal lags increase our confidence in the temporal ordering of the observed patterns but caution is needed in interpreting coefficients in a strict causal sense.

Leave-One-Out Cross-Validation and Permutation Tests. Because we consider multiple types of interdependencies between community areas in the form of spatial and network lags, the assumption required by regular regression approaches that observations are independent is not reasonable. Although approaches exist for handling spatial interdependencies with negative binomial regression, combining spatial and network indices introduces new interdependencies. To deal with this challenge, we use a technique common in computational statistics and machine learning, though less so in criminology, to separate the training data (used to fit the model) from the test data (used to evaluate model accuracy) (Hastie, Tibshirani, & Friedman, 2009).

The quality of a model is often estimated using a standard in-sample estimator like the Akaike Information Criterion (AIC), which adjusts for model complexity to counter the effects of overfitting and get more accurate estimates of error. However, because AIC is derived from an asymptotic analysis based on independent records, it requires large sample sizes and may be affected by interdependencies between observations (DeLeeuw, 1992). Thus, in addition to comparing AIC scores across models, we also evaluate model accuracy by comparing estimates of absolute reduction in error and relative reduction in error using *leave-one-out cross-validation*, which allows us to measure error out-of-sample. Leave-one-out cross-validation (Hastie et al., 2009) yields more accurate error estimates compared to typical in-sample estimates because the model is not evaluated on the same data it was trained.

For N community areas, the model error is estimated using the following procedure. For each community area C_i, we fit the model on the other community areas (by temporarily removing C_i from the data) and then we evaluate the model's accuracy on C_i. Repeating this procedure for each of the N community areas yields N error estimates that are averaged. Specifically, the mean absolute error (MAE) is calculated by taking the sum of the absolute value of the difference between each observation and its predicted value and then dividing it by the sample size: MAE = $\sum_i^n |y_i - \hat{y_i}| \ / N$, y_i refers to the crime index score for each C_i. The mean relative error (MRE) is calculated by taking the sum of the relative errors and then dividing by the sample size. The relative error is calculated by taking the absolute value of the difference between each observation and its predicted value, and then dividing by the observed value: MRE = $\sum_i^n (|y_i - \hat{y_i}|/y_i) \ /N$. In other words, we measure how well a model based on the rest of the community areas predicts crime in a community area on which it was not trained. This approach is designed to detect overfitting and does not need adjustments for model complexity. Without using leave-one-out, the model would be tested on a point it was trained on, and would have the ability to memorize the testing points. Such memorization would produce unusually optimistic error estimates. This scenario is prevented by leave-one-out.

Leave-one-out cross-validation gives model level error estimates, but not significance estimates for the predictors of interest. Thus, we next use permutation tests from computational statistics (Breiman, 2001). The goal of permutations is to take a predicting variable (feature) and make it independent from the dependent variable (target) by permuting the feature. We conduct multiple permutations and measure error for each permutation, which creates a null distribution of what the errors would look like if that predictor variable were independent of the target variable. The null hypothesis is that the inclusion of a variable does not improve model accuracy. The test statistic for p-value computation is the MAE. Hence, we are testing the significance of a variable on model accuracy. To obtain samples from the null distribution, we permute the value of that variable randomly (using a uniform distribution over permutations) across community areas (thus breaking any predictive value that the variable could have). For every permutation, we fit the model and measure accuracy. Repeating the permutation technique M times gives us M empirical samples from the null distribution. We then compare the accuracy on the original data to these M samples under the null distribution. The p value is the fraction of values from the null distribution that are greater than or equal to the accuracy on the original data and measures whether the inclusion of a variable reduces error in a statistically significant way.

Analytical Strategy. We conduct analyses using the following sequence of steps in order to test our hypotheses and conduct robustness tests. First, we estimate the bivariate relationship between network disadvantage and crime using a negative binomial model without controls. Next, we gradually include other variables (Table 2) to determine the extent to which the initially observed connection between the main predictive variable of interest and the outcome may be explained by any controls. If sociodemographic controls influence both network disadvantage and internal disadvantage, they may confound the initially observed relationship between network disadvantage and local crime. If measures such as network crime or spatial contiguity to disadvantage explain, or perhaps mediate, the relationship between network disadvantage and crime, the extent to which the initial association between network disadvantage and crime changes after adding these measures, is theoretically instructive. We also assess whether the main effects are consistent among periods of time during the study. In subsequent models, we add temporal lags to estimate differences in crime over time, focusing on the overall crime and on different crime types (Table 3). Next, we use computational tests to compare the accuracy of models of gradually increased complexity using MAE, MRE and AIC (Table 4). We start with models that only include demographics, move to models that add surrounding disadvantage and crime; then we include network crime; add temporal lag; and finally, we estimate error reduction based on models that add network disadvantage. Finally, we move from a focus on each model overall to a focus on individual variables and conduct a series of permutation tests to assess the extent to which the inclusion of a variable significantly reduces error (Table 5).

RESULTS

Crime decreased during our study period across Chicago's communities (Table 1), which is consistent with the national downward trend of crime. The decline is observed for the internal crime levels of communities, their network crime levels, and surrounding crime levels. Average network crime values tend to be higher than average surrounding crime, suggesting that models accounting for spatial spillovers but not for network spillovers may miss important extra-local crime exposures. Conversely, average network disadvantage (-.42 in 2004) is lower than average surrounding disadvantage (-.01) and internal disadvantage (-.04), suggesting a reason why some disadvantaged areas may be more protected from crime than others. Further examinations show that neighborhoods with above-median levels of both internal and network disadvantage (38% of all communities in 2004) have significantly higher rates of crime than areas with above-median internal disadvantage but below-median network disadvantage (12%), suggesting that including network disadvantage in modeling crime may improve our understanding of crime.

<Table 1 about here>

Further descriptive analyses also shed light on the ways in which neighborhoods are connected and how network disadvantage varies by residential neighborhood disadvantage. Generally, the most disadvantaged residential neighborhoods are least likely to have connections to the most affluent places. Communities in the highest internal disadvantage thirtile have the highest network disadvantage levels. For instance, in 2004, the median network disadvantage was -.26, mean -.29; standard deviation (SD).10, minimum -.53, maximum -.14. Those in the middle internal disadvantage thirtile showed a median network disadvantage of -.35, mean -.41; SD of .15, minimum of -.71, maximum of -.19. Those in the lowest internal disadvantage thirtile exhibit the lowest median network disadvantage level of -.60; a mean of -.56, SD .13, minimum -.72 and maximum -.27. Overall, the median and average network disadvantage levels are highest for residential neighborhoods with the highest disadvantage and lowest for the most affluent residential neighborhoods. This is not particularly surprising considering existing research on homophily in ties, research on employment discrimination based on area of residence, and our focus on low-income commuting ties. However, there are also some important variations from this general pattern. For instance, in 2004, of the 26 residential community areas in the highest thirtile of disadvantage, 31% show an average connectedness to better-off work communities, in the middle (6) or lower (2) thirtile of network disadvantage levels. Likewise, of the 26 residential community areas in the lowest disadvantage thirtile, 35% are connected to communities of higher disadvantage on average, in the middle (8) or highest thirtile (1) of network disadvantage.

A similar pattern is observed when separating communities at the median disadvantage levels, with over 23% of the residential communities in the top disadvantage level category connected on average with communities in the bottom level of network disadvantage, and vice-versa.

Next, we estimate a series of negative binomial models in which we gradually add other neighborhood covariates to test our hypotheses. The first model of Table 2 shows that network disadvantage is positively and strongly associated with local area crime level during the first period in our study, 2004-06. For each one-standard deviation increase in network disadvantage, the expected increase in overall crime is .455 units. Exponentiating this coefficient gives a value of 1.576, which means that a standard deviation increase in network disadvantage is associated with a 58% increase in overall crime rate (Osgood, 2000). This is consistent with the first hypothesis, that work network disadvantage is positively associated with local crime.

Model 2 adds controls for internal residential demographics and internal disadvantage. The effect of network disadvantage decreases, as expected, but remains positive and significant. Specifically, a one-standard deviation increase in network disadvantage increases overall crime .248 units, corresponding to a 28% increase in the overall crime rate. The internal disadvantage also has a significant positive effect, with a one-standard deviation increase leading to a .145 unit increase in overall crime. Population density, residential stability, and ethnic diversity all have a negative coefficient, which means that one unit increase in each of these demographic variables predicts a significant decrease in the overall crime rate. In sum, these patterns indicate that local disadvantage explains some but not all of the association between network disadvantage and local crime, in partial support of the *selective homophily* hypothesis 2. By showing that network disadvantage increases crime in a home community independent of internal disadvantage and other demographics, the results add further support for the *work network* hypothesis 1.

Model 3 of Table 2 adds surrounding disadvantage to the variables included in Model 2. Results show the coefficient of surrounding disadvantage (.089) does not reach significance, but its inclusion does slightly decrease the magnitude and significance of the network disadvantage coefficient (.208). Thus, the results indicate that even though a part of the role of network disadvantage in predicting higher levels of crime may be mediated by spatial spillovers of disadvantage, the network disadvantage effect remains strong and significant. Model 4 of Table 2 additionally controls for surrounding and network crime. The coefficient of surrounding crime (.134) is positive and significant, but the network crime coefficient (.103) is not. The magnitude of the coefficient of network disadvantage decreases somewhat (.161), but remains significant ($p<.05$). In sum, these results indicate that the role of network disadvantage in predicting higher levels of crime in the home community is robust to controlling for spatial and network spillovers of crime. These patterns thus offer only weak support for the *geographic and network crime spillover* hypotheses 3 and 4 and further support the *work network* hypothesis 1.

The role of network disadvantage is stably positive and significant over time in predicting crime in 3-year spells between 2004 and 2013. Model estimates presented in Table 2 and corresponding models estimating crime year-by-year (Appendix Table 1 Model 1) show broadly the same patterns of results as before, suggesting stability in effects across most of the years during the study. Some minor exceptions emerge for two of the 11 years. In predicting 2005 violent crime the coefficient of network disadvantage is non-significant and for overall crime in 2005 and 2013 the coefficient is marginally significant.

<Table 2 about here>

Next, Table 3 shows results from estimating models of different types of crime in 2004-06 and 2011-13 while controlling for the same measures as in Model 4 of Table 2 as well as for the prior level of the corresponding type of crime. The coefficients for network disadvantage are positive and significant for models predicting overall crime. The coefficient for network disadvantage in predicting overall crime is .162 for 2004-06 and .233 for 2011-13. Analyses for the intermediary time periods (available at request) yield the same pattern of results. Together, the results indicate that the role of network disadvantage in predicting higher levels of crime is robust to controlling for prior levels of crime and stable in its significance over time. This suggests that network disadvantage increases crime over time and its effects may be robust to controlling for unmeasured characteristics that contributed to prior levels of crime.

The next models of Table 3 show results from analyses of the role of network disadvantage in predicting not just overall crime incidents but also violent crime, robbery, homicide, and property crime separately across the years. The coefficients for network disadvantage in predicting violent crime are: .217 in 2004-06 and .238 in 2011-13; in predicting robbery: .291 in 2004-06 and .278 in 2011-13; in predicting homicide: .347 in 2004-06 and .481 in 2011-13; and for property crime: .237 in 2004-06 and .280 in 2011-13. These results indicate that the role of network disadvantage is positive and significant in predicting not just overall crime incidents but various crime types separately. This suggests that the results are not sensitive to measurement error in reporting violence (Baumer, 2002; Baumer & Lauritsen, 2010).

Table 4 compares the performance of models with gradually more predictors in estimating overall crime, violent crime, and property crime across different time periods during our study. The sequence starts with Model 1 that only includes internal disadvantage and other demographic characteristics; then, moves to Model 2 that adds surrounding disadvantage and crime to the set of variables in Model 1; Model 3 adds network crime; Model 4 adds temporal lag of crime; and Model 5 adds network disadvantage. Results indicate that models that include network disadvantage tend to have a higher accuracy (lowest errors and lowest AIC scores) in predicting overall crime, violent crime, and property crime compared to the other models. This pattern is not perfectly consistent across all year-crime-type combinations. For instance, in predicting overall crime in 2004-06, the Model 5's MAE is the third lowest. However, in Model 5 for 2004-06 violent crime, the value for the MAE is 451.368, the value for the MRE is .336, and the AIC is 1148.7, all of which are lower than the values in any of the other four models. The same is the case for 2004-06 property crime. The MAE levels seem less stable over time, but not for violent crime and less so for property crime. Still, no other model matches the accuracy of the network disadvantage Model 5 on all three indicators, across crime types and years.

<Tables 4 and 5 about here>

Table 5 shows results from estimations using the leave-one-out method with 1000 permutations. A low p value indicates that including the corresponding variable significantly improves model accuracy (reduces error). Similar patterns for network disadvantage emerge in these models as in all previous models. Network disadvantage generally has a significant and positive effect on predicting crime, across crime types and years, with the exception of overall crime in 2004-06. For example, the coefficient for network disadvantage for violent crime in 2004-06 is .217 and the significance value is .007. This value means that about .7% of the values of model accuracy from the null distribution generated from the permutation distribution are greater than or equal to the accuracy on the original data. Thus, including network disadvantage in the model leads to a significant reduction in model error. These additional tests add further confidence in the results above in support of the *work network* hypothesis 1.

Multicollinearity diagnostics suggest that collinearity is of little concern. Still, in supplementary analyses we also a) excluded spatially proximate areas from the network index and b) created a residual network measure, with similar results as before (see below).

Supplementary Analyses. We conducted a series of supplementary analyses, summarized below and described in the Online Appendix in more detail. First, we estimated a set of models predicting yearly crime levels and found the same pattern of results as before. Segregation. Second, analyses that added measures of racial and ethnic composition of neighborhoods to the previous set of controls indicated the same result patterns as before. We also ran models with added controls for high segregation indicated by whether communities are over 60% black or over 60% Hispanic, and network disadvantage remains significant and positive across all time periods. Additional controls. Models with *median household income* as an additional control showed similar results. We also considered the potential effect of the number of *retail businesses* in a given community area, which could influence the level of crime, with little change in results.

Demographic differences. To assess possible differences in network spillover effects by income and age categories, we created additional measures based on information in the LODES commuter data about broad categories of income and age. Models with these measures were consistent with the general pattern. Notably, results suggest that low income ties constitute stronger pathways of influence in the spatial distribution of crime across the city and that, possibly, higher income or the middle-age status may buffer against the negative effects of commuting to disadvantaged work areas. Non-linear effects. To assess non-linear effects, we separated network disadvantage into thirtiles and found that the highest thirtile was significantly stronger than the lowest in predicting overall crime across most time periods. Additionally, modeling the interaction between high, medium, and low internal disadvantage and continuous network disadvantage suggested some possible nonlinearity, but more research is needed.

Network spillovers v. spatial spillovers. We also re-calculated network disadvantage to include only non-contiguous areas from the commuting network and re-estimated the core models. Surrounding disadvantage becomes significantly associated with overall crime across several years, which suggests that the original index was likely picking up some of the effect of surrounding disadvantage. Still, the network disadvantage effect remains significant and positive.

Selection. In the absence of randomized data, the main models accounted for selection in several ways. First, we include controls for a) socioeconomic and demographic characteristics; b) internal (and surrounding) disadvantage to account for possible homophily in employment outcomes; and c) prior levels of crime, which implicitly controls for measured and unmeasured social determinants of prior crime. Additionally, we estimated multilevel negative binomial regression models using all time periods pooled together, with robust standard errors and period fixed effects that otherwise matched our core models. This approach yielded a similar pattern in the core results as before. Endogeneity. We address potential concerns about endogeneity and spatial multiplier processes through a negative binomial approach, combined with leave-one-out cross-validation and permutations in the core analyses. Additionally, we used more standard spatial modeling approaches in supplementary analyses (Anselin et al., 2000). Using a spatial weight matrix based on the Queen criterion, we estimated crime rates using a maximum likelihood spatial lag modeling approach in GeoDa (Anselin et al., 2006). Results from models that control for all the internal conditions and the spatial lag of the dependent variable match the previous results. To account for network endogeneity, we used generalized spatial two-stage least squares estimation approaches in Stata, in which we replaced the spatial weights matrix with a network weights matrix. With minor variations, the results are consistent with the previous patterns. FBI definitions. Next, we dug deeper into the FBI and Chicago PD definitions of each crime type and selected only the reported crimes that fit best with the FBI crime definitions of violent crime and property crime, with little change in the results.

Network spillovers v. internal or surrounding effects. We calculated a residual network disadvantage measure based on a regression of network disadvantage on internal disadvantage and surrounding disadvantage and re-estimated the fully controlled models using this measure instead of the original network disadvantage. The coefficients of the new measure were, as expected, smaller in magnitude for network disadvantage but remained positive and significant.

DISCUSSION

This study showed evidence that the disadvantage levels in the extra-local network of communities where people work predicts higher levels of crime in people's home communities. The patterns are broadly consistent across different crime types and years and robust to controlling for internal levels of concentrated disadvantage and other structural measures of social disorganization such as residential stability and population heterogeneity. The effect of network disadvantage is consistent with prior expectations from work on activity spaces, public control, social disorganization, and routine activities, and further extends this work to highlight for the first time the significance for crime of extra-local forces related to commuting.

The findings suggest that if residents of a focal neighborhood are exposed at work to low disadvantage and, presumably, to social organization forces such as high social cohesion and trust (Sampson, Morenoff, & Gannon-Rowley, 2002; Sampson et al., 1997), they may apply these ideas at home and try similar strategies to control crime. Such a pattern exists in health studies of workers, who apply strategies learned at work related to healthy eating (Buller et al., 2000) or quitting smoking (Kouvonen et al., 2008) to their own lives. Workers' new knowledge or behavior may also influence others (Christakis & Fowler, 2013). When enough residents have positive exposures, a momentum may be created for local change. When, instead, people experience disorder and mistrust at work, it may increase strain and anomie (Agnew, 1999; Merton, 1938) leading to disengagement, frustration, or fights at home (Bolger et al., 1989).

Residents' exposures to less disadvantaged outside work environments may also contribute to lower local crime if such exposures increase access to external resources, services, and organizations that may not otherwise be available. This idea is consistent with classic thinking on social isolation (Wilson, 1987) and with research showing that increasing residents' participation in organizations and services decreases aggression and reduces crime (Molnar et al., 2008; Witt & Crompton, 1996). Residents' access to resources and institutions at work may mitigate the deprivation and strain effects of institutional deficiencies at home. The findings also support existing insights on *public control* (Hunter, 1985) and are consistent with evidence that external resources like home mortgage lending or ties to public officials and the police can decrease local crime (Vélez, 2001; Vélez et al., 2012). Ties to influential outside actors can be consequential in securing resources to improve the neighborhood (e.g., clean up brownfields) or prevent political decisions like building a highway through the neighborhood that would displace people and decrease remaining home values (Logan & Molotch, 1987).

The results suggest that the initially observed association between network disadvantage and crime may also be in part explained by *spatial and network spillovers*. As disadvantage in work communities increases crime there, motivated offenders (or victims) may travel through commuting channels in search for targets (or safer activity locations). This is consistent with insights on routine activities (Cohen & Felson, 1979), crime pattern theory (Beavon et al. 1994; Brantingham & Brantingham, 1995), and empirical research that suggests that crime often occurs outside the area of offenders' or victims' residence (Tita & Griffiths, 2005). The findings also relate to prior work on routine activities and transportation flows and crime, including finding that taxi trips help predict crime (Wang et al., 2016) and that people's travel patterns to work are correlated with violent and property crime (Felson and Boivin, 2015). Still, the network disadvantage spillovers are not explained away by crime spillovers over the same network.

Beyond the independent effect of work network disadvantage on local crime, the findings also show that the initial observed effects of network disadvantage can be in part explained by its association with internal disadvantage. This is consistent with prior findings that communities tend to be connected to similarly disadvantaged others (Graif et al., 2017; Schaefer, 2012) and that residents of disadvantaged communities tend to conduct routine activities in similarly disadvantaged areas (Krivo et al., 2013). The findings also suggest that the effects of network spillovers of disadvantage may be partly related to the *geographic proximity* of some of the residents' work areas. This is consistent with an increasing body of evidence that disadvantage in geographically proximate areas is significantly related to victimization, delinquency, crime, and other health risks in a neighborhood (Crowder & South, 2011; Morenoff, Sampson, & Raudenbush, 2001; Peterson & Krivo, 2009, 2010; Vogel & South, 2016). The results are also consistent with evidence that crime is affected by poverty several miles away (Graif and Matthews, 2017), and suggest that activity spaces may explain some of the geographic spillovers.

Results also show that work network disadvantage predicts higher levels of crime while controlling for prior levels of local crime. This suggests that work network disadvantage contributes to increases in local crime over time and its effects may be robust to controlling for unmeasured characteristics that may have contributed to prior levels of crime.

Limitations. Future work will benefit from comparing patterns at different geographic sizes to speak to current methodological and classical theoretical debates on the importance of communities of different scales (Hipp, 2007; Hunter & Suttles, 1972). Caution is needed in interpreting the results as causal. The longitudinal design of the study and the controls for prior crime levels help indicate the temporal order of the observed patterns but further research is needed on testing possible causal mechanisms. For example, learning about a neighborhood watch in a work community may influence commuters to start such a group in their home community. Testing the underlying mechanisms is beyond the scope of this study but is a valuable direction for future research (Hedstrom & Ylikoski, 2010; Matsueda, 2017).

The crime data is limited to neighborhoods within the city, a common limitation in communities and crime studies. Overcoming this limitation would help illuminate differences between suburbs and inner-city neighborhood dynamics (Singer, 2014). Although Chicago has the advantage of size and diversity, its segregation levels make the generalizability of the findings to other cities uncertain. Future analyses comparing effects of network disadvantage among different cities, large versus small, and urban versus suburban versus rural communities will be invaluable. An important direction for future research is also to further differentiate between different types of ties, including strong and weak. It would also be useful to include more demographic data about commuters. Commuting is uniquely valuable as a direct measure of how working residents cross neighborhood boundaries on a routine basis, but other types of activity-based connections relevant for the public control of crime are likely important as well. Future research that assesses different types of activity locations, such as travel related to recreation or other activities, and data sources (e.g., using Uber, Lyft, or other taxi trips; Twitter and Facebook check-in locations) will be valuable. Adding such organic big data will be invaluable in complementing high-cost prospective activity space data. Finally, the focus on origin-destination points leaves open questions about the relevance of the places situated on the commuters' route between home and work.

CONTRIBUTIONS AND IMPLICATIONS

Motivated by a rapidly growing interest in a relational ecology of neighborhood effects in criminology and beyond (Browning et al., 2017; Sampson, 2012) the current study examined the extent to which the ecological network contexts of neighborhoods significantly contribute to local crime. Results from analyses of networks based on commuting flows among Chicago neighborhoods over more than a decade showed that local crime is positively associated with concentrated disadvantage in communities where residents go to work, independent of internal disadvantage, spatial spillovers, and prior crime levels. These findings contribute to the literature in several key ways and have significant implications for future research and policy. First, the results suggest that network exposures are relevant for crime above and beyond the effects of internal disadvantage and geographically proximate spillovers -- the two major explanatory forces in the neighborhood effects and communities and crime literature to date. This highlights the importance of revisiting assumptions in the literature of neighborhoods as *closed systems* or as *simply affected by spillovers from nearby areas* (Browning, et al., 2017; Graif et al., 2014).

Second, the results connect with and advance the *routine activities, crime pattern,* and *activity space* bodies of work (Boivin & D'Elia, 2017; Browning, Calder, Soller, et al., 2017; Browning et al., 2015; Cohen & Felson, 1979; Felson & Boivin 2015; Krivo et al., 2013; Wikström et al., 2010) by showing for the first time the significant neighborhood level implications of residents' daily mobility across space through activities such as commuting for work. Considering the costs of collecting activity space data through surveys, our study shows that using administrative data on commuting is a valuable, scalable, and feasible approach. The focus on employment-based activity spaces, while limited in the breadth of activities and exposures it can capture, reflects a major activity in which people spend many of their waking hours (Lindström, 2008). Importantly, people also develop a wider range of weak ties at work, which may be important in information transmission and norms diffusion (Granovetter, 1973).

These findings also contribute to the current criminological knowledge on communities and place and to the spatial and neighborhood effects literature more broadly by showing evidence suggesting that disadvantage risks may spillover through population mobility channels that are not accounted for in the traditional neighborhood effects approaches. The current study builds on recent advances in spatial modeling (Graif, 2015; Morenoff et al., 2001; Peterson & Krivo, 2009) and pushes the field further by revisiting implicit assumptions of interactions across space to *explicitly* model interactions across space, via commuting.

Furthermore, the study connects to recent work on transportation and crime (Boivin & Felson, 2017) and expands it by moving beyond a focus on crime traveling through transportation channels to highlight for the first time the effects on crime of the disadvantage exposures through such channels. By pushing beyond geographic proximity and showing evidence in support of broader avenues of extra-local influence, the current findings support and advance a classic perspective on public social control (Hunter, 1985) -- a fundamental but under-explored category of mechanisms that complement rather than exclude the more commonly examined private and parochial forms of control (e.g., Vélez, 2001).

These results are also consistent with an emerging body of work on the importance of networks across space based on co-offending or gang conflicts (Papachristos, 2015; Papachristos et al., 2013; Schaefer, 2012) and further extend the literature by demonstrating the importance of commuting ties across neighborhoods. Commuting dynamics present promising new possibilities for crime control because, compared to co-offending or gang conflicts, which are rare and negative forms of interactions, commuting is a more *frequent and routine* (predictable) form of interaction, with many possible positive implications. The results support the idea that extra-local resources and information flow through commuting networks to shape crime (Vélez et al., 2012).

The current findings suggest that new avenues for decreasing neighborhood crime may be possible through an area's connections to other areas. Much attention has been paid to the recent increasing levels of crime in some Chicago communities, despite the overall downward trend in crime across the country (e.g., Gorner, 2016a, b; Wills & Hernandez, 2017), suggesting that some local approaches need refining. To control crime, this study suggests that attention must be paid not only to a community's disadvantage level but also to the disadvantage level in the communities to which residents are exposed at work. When residents of poor areas have jobs in other disadvantaged areas, the effects of crime at home may be harder to overcome than when jobs are in less disadvantaged areas. Programs that encourage connections between areas of different disadvantage levels may open new avenues for crime prevention and control.

The findings suggest that where people go to work can affect safety in their own neighborhoods. By focusing on the interconnectedness of neighborhoods and the disadvantage spillovers through such networks, programs that intervene in well-connected neighborhoods may lower crime in many more neighborhoods, ultimately benefitting the city as a whole. Through work ties, parents in disadvantaged neighborhoods may begin to access extra-local resources, services, and information that can protect them and their children from victimization or involvement in crime (Harding, 2010). Although it may be challenging to convince employers to bring jobs to a disadvantaged neighborhood, it may be feasible to improve the neighborhood's connections (e.g., public transportation) to less disadvantaged areas where jobs are located, and to incentivize employers to hire workers from disadvantaged areas.

Future research will also benefit from further extending the models of ecological network dynamics proposed here to investigate possible heterogeneity in effects across different cities and periods. Qualitative and quantitative work will be needed to further understand the mechanisms of social interactions that contribute to the observed effects of work network disadvantage.

REFERENCES

Abowd, J. M., Stephens, B. E., Vilhuber, L., Andersson, F., McKinney, K. L., Roemer, M., & Woodcock, S. (2009). The LEHD infrastructure files and the creation of the quarterly workforce indicators. In T. Dunne, J. B. Jensen, & M. J. Roberts (Eds.), *Producer Dynamics: New Evidence from Micro Data* (pp. 149-230). University of Chicago Press.

Agnew, R. (1999). A general strain theory of community differences in crime rates. *Journal of Research in Crime and Delinquency, 36*, 123-155.

Anselin, L. (2002). Under the hood issues in the specification and interpretation of spatial regression models. *Agricultural Economics, 27*, 247-267.

Anselin, L., Cohen, J., Cook, D., Gorr, W., & Tita, G. (2000). Spatial analyses of crime. *Criminal Justice, 4*, 213-262.

Anselin, L., Syabri, I., & Kho, Y. (2006) GeoDa: an introduction to spatial data analysis. *Geographical Analysis 38*(1), 5-22.

Baumer, E. P. (2002). Neighborhood disadvantage and police notification by victims of violence. *Criminology, 40*, 579-616.

Baumer, E. P., & Lauritsen, J. L. (2010). Reporting crime to the police, 1973-2005: A multivariate analysis of long-term trends in the national crime survey (NCS) and national crime victimization survey (NCVS). *Criminology, 48,* 131-185.

Beavon, D. J. K., Brantingham, P. L., & Brantingham, P. J. (1994). The influence of street networks on the patterning of property offenses. *Crime Prevention Studies, 2*, 115-148.

Bennett, T., Holloway, K., & Farrington, D. P. (2006). Does neighborhood watch reduce crime? A systematic review and meta-analysis. *Journal of Experimental Criminology, 2*, 437-458.

Bernasco, W., and Block, R. (2011). Robberies in Chicago: A block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. *Journal of Research in Crime and Delinquency 48*(1), 33-57.

Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination. *American Economic Review, 94*, 991-1013.

Besbris, M., Faber, J. W., Rich, P., & Sharkey, P. (2015). Effect of neighborhood stigma on economic transactions. *Proceedings of the National Academy of Sciences of the United States of America, 112*, 4994-4998.

Blau, P. M. (1977). *Inequality and Heterogeneity: A Primitive Theory of Social Structure*, vol. 7. New York: Free Press.

Boessen, A., & Hipp, J. R. (2015). Close-ups and the scale of ecology: Land uses and the geography of social context and crime. *Criminology, 53*, 399-426.

Boivin, R., & Felson, M. (2017). Crimes by visitors versus crimes by residents: The influence of visitor inflows. *Journal of Quantitative Criminology*. Advance online publication. Retrieved from https://link.springer.com/article/10.1007/s10940-017-9341-1

Boivin, R., & D'Elia, M. (2017). A network of neighborhoods: Predicting crime trips in a large Canadian city. *Journal of Research in Crime and Delinquency, 54*, 824-846.

Bolger, N., DeLongis, A., Kessler, R. C., & Wethington, E. (1989). The contagion of stress across multiple roles. *Journal of Marriage and Family, 51*, 175-183.
Brantingham, P. L., & Brantingham, P. J. (1995). Criminality of place. *European Journal on Criminal Policy and Research, 3*, 5-26.
Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5-32.
Browning, C. R., & Soller, B. (2014). Moving beyond neighborhood: Activity spaces and ecological networks as contexts for youth development. *Cityscape, 16*, 165-196.
Browning, C. R., Soller, B., & Jackson, A. L. (2015). Neighborhoods and adolescent health-risk behavior: An ecological networks approach. *Social Science & Medicine, 125*, 163-172.
Browning, C. R., Calder, C. A., Boettner, B., & Smith, A. (2017). Ecological networks and urban crime: The structure of shared routines activity locations and neighborhood-level informal control capacity. *Criminology, 55*, 754-778.
Browning, C. R., Calder, C. A., Soller, B., Jackson, A. L, & Dirlam, J. (2017). Ecological networks and neighborhood social organization. *American Journal of Sociology, 122*,1939-88.
Buller, D., Buller, M. K., Larkey, L., Sennott-Miller, L., Taren, D., Aickin, M., Wentzel, T. M., & Morrill, C. (2000). Implementing a 5-a-day peer health educator program for public sector labor and trades employees. *Health Education & Behavior, 27*, 232-240.
Bursik Jr, R. J., & Grasmick, H. G. (1993). *Neighborhoods and Crime*. Lexington Books.
Christakis, N. A., & Fowler, J. H. (2013). Social contagion theory: Examining dynamic social networks and human behavior. *Statistics in Medicine, 32*, 556-577.
Cisneros, H. (1996). Defensible space: Deterring crime & building community.*Cityscape,*15-33.
Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*, 588-608.
Crowder, K., & South, S. J. (2011). Spatial and temporal dimensions of neighborhood effects on high school graduation. *Social Science Research, 40*, 87-106.
Crowe, T. D. (2000). *Crime Prevention through Environmental Design: Applications of Architectural Design and Space Management Concepts* (2nd ed.). Boston, MA: Butterworth.
DeLeeuw, J. (1992). Introduction to Akaike (1973) information theory and an extension of the maximum likelihood principle. In S. Kotz, & N. L. Johnson (Eds.), *Breakthroughs in Statistics: Foundations and Basic Theory*, (Vol. 1). New York: Springer Series in Statistics.
Feller, W. (1943). On a general class of contagious distributions. *Annals of Mathematical Statistics 14*, 389–400.
Felson, M., & Boivin, R. (2015). Daily crime flows within a city. *Crime Science, 4,* 1-10.
Gorner, J. (2016a, January 2). Chicago violence, homicides, and shootings up in 2015. *The Chicago Tribune*. Retrieved from http://www.chicagotribune.com
Gorner, J. (2016b, December 30). Few answers as Chicago hit with worst violence in nearly 20 years. *The Chicago Tribune*. Retrieved from http://www.chicagotribune.com
Gould, R. V. (1991). Multiple networks and mobilization in the Paris Commune, 1871. *American Sociological Review, 56*, 716-729.
Graif, C. (2015). Delinquency and gender moderation in the moving to opportunity intervention: The role of extended neighborhoods. *Criminology, 53,* 366–398.
Graif, C., Gladfelter, A. S., & Matthews, S. A. (2014). Urban poverty and neighborhood effects on crime: Incorporating spatial and network perspectives. *Sociology Compass, 8,* 1140-1155.
Graif, C., Lungeanu, A., & Yetter, A. M. (2017). Neighborhood isolation in Chicago: Violent crime effects on structural isolation and homophily in inter-neighborhood commuting networks. *Social Networks, 51,* 40-59.

Graif, C., & Matthews, S. A. (2017). The long arm of poverty: Extended and relational geographies of child victimization and neighborhood violence exposures. *Justice Quarterly, 34*, 1096-1125.
Granovetter, M.S. (1973). The strength of weak ties. *American Journal of Sociology,78:*1360-80.
Groff, E. R., & Lockwood, B. (2014). Criminogenic facilities and crime across street segments in Philadelphia: Uncovering evidence about the spatial extent of facility influence. *Journal of Research in Crime and Delinquency, 51,* 277-314.
Groff, E. R., & McEwen, T. (2007). Integrating distance into mobility triangle typologies. *Social Science Computer Review, 25,* 210-238.
Haberman, C. P., & Ratcliffe, J. H. (2015). Testing for temporally differentiated relationships among potentially criminogenic places and census block street robbery counts. *Criminology, 53,* 457-483.
Harding, D. J. (2010). *Living the Drama: Community, conflict, and culture among inner-city boys*. Chicago, IL: University of Chicago Press.
Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (2nd ed.). Berlin: Springer Series in Statistics.
Hedström, P., & Ylikoski, P. (2010). Causal mechanisms in the social sciences. *Annual Review of Sociology, 36,* 49-67.
Hipp, J. R. (2007). Block, tract, and levels of aggregation: Neighborhood structure and crime and disorder as a case in point. *American Sociological Review*, *72*(5), 659-680.
Hipp, J. R., & Boessen, A. (2015). Neighborhoods, social networks and crime. In F. T. Cullen, P. Wilcox, R. J. Sampson, & B. D. Dooley (Eds.), *Challenging Criminological Theory: The Legacy of Ruth Kornhauser* (pp. 275-98). New Brunswick, NJ: Transaction Publishers.
Hoeben, E. M., & Weerman, F. M. (2016). Why is involvement in unstructured socializing related to adolescent delinquency? *Criminology, 54,* 242-281.
House, J. S., & Smith, D. A. (1989). Evaluating the health effects of demanding work on and off the job. In T. F. Drury (Ed.), *Assessing Physical Fitness and Physical Activity in Population-Based Surveys*. Hyattsville, MD: National Center for Health Statistics.
Hunter, A. J. (1985). Private, parochial, and public social orders: The problem of crime and incivility in urban communities. In G. D. Suttles and M. Zald (Eds.), *The Challenge of Social Control: Citizenship and Institution Building in Modern Society*. Norwood, NJ: Ablex.
Hunter, A.D., & Suttles, G. (1972). “The Expanding Community of Limited Liability.” In G. Suttles (Ed.), *The Social Construction of Communities* (pp. 44-81). Univ. of Chicago Press.
Hunter, A. D. (1974). Symbolic communities: The persistence and change of Chicago's local communities. University of Chicago Press.
Kouvonen, A., Oksanen, T., Vahtera, J., Väänänen, A., De Vogli, R., Elovainio, M., Pentti, J., Leka, S., Cox, T., & Kivimäki, M. (2008). Work-place social capital and smoking cessation: The Finnish Public Sector Study. *Addiction, 103,* 1857-1865.
Krivo, L. J., Washington, H. M., Peterson, R. D., Browning, C. R., Calder, C. A., & Kwan, M. P. (2013). Social isolation of disadvantage and advantage: The reproduction of inequality in urban space. *Social Forces, 92,* 141-164.
LeBlanc, M. M., & Kelloway, E. K. (2002). Predictors and outcomes of workplace violence and aggression. *Journal of Applied Psychology, 87,* 444-453.
Lindström, M. (2008). Invited commentary: Social capital, social contexts, and depression. *American Journal of Epidemiology, 167,* 1152-1154.
Logan, J. R., & Molotch, H. L. (1987). *Urban Fortunes: The Political Economy of Place*

Los Angeles, CA: University of California Press.
Marks, S. R. (1994). Intimacy in the public realm: The case of co-workers. *Social Forces 72,* 843-58.
Matsueda, Ross L. (2017). Toward an analytical criminology: the micro–macro problem, causal mechanisms, and public policy." *Criminology 55*(3), 493-519.
Matthews, S. A., & Yang, T. S. (2013). Spatial polygamy and contextual exposures (SPACEs): Promoting activity space approaches in research on place and health. *American Behavioral Scientist, 57,* 1057-1081.
Matthews, S. A., Yang, T. S., Hayslett, K. L., & Ruback, R. B. (2010). Built environment and property crime in Seattle, 1998–2000: A Bayesian analysis. *Environment and Planning A, 42,* 1403-1420.
Mears, D. P., & Bhati, A. S. (2006). No community is an island: The effects of resource deprivation on urban violence in spatially and socially proximate communities. *Criminology, 44*, 509-548.
Merton, R. K. (1938). Social structure and anomie. *American Sociological Review, 3,* 672-682.
Molnar, B. E., Cerda, M., Roberts, A. L, & Buka, S. L. (2008). Effects of neighborhood resources on aggressive and delinquent behaviors among urban youths. *American Journal of Public Health, 98,* 1086-1093.
Morenoff, J. D., Sampson, R. J., & Raudenbush, S. W. (2001). Neighborhood inequality, collective efficacy, and spatial dynamics of urban violence. *Criminology, 39,* 517-558.
Ong, P. M. (1996). Work and car ownership among welfare recipients. *Social Work Research, 20*, 255-262.
Osgood, D. W. (2000). Poisson-based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology, 16*, 21-43.
Owens, B. R. (2012). Mapping the city: Innovation and continuity in the Chicago School of Sociology, 1920–1934. *The American Sociologist 43*(3), 264-293.
Papachristos, A. V. (2015). The company you keep? The spillover effects of gang membership on individual gunshot victimization in a co-offending network. *Criminology, 53*, 624-649.
Papachristos, A. V., Hureau, D. M., & Braga, A. A. (2013). The corner and the crew: The influence of geography and social networks on gang violence. *American Sociological Review, 78*, 417-447.
Peterson, R. D., & Krivo, L. J. (2009). Segregated spatial locations, race-ethnic composition, and neighborhood violent crime. *Annals of the AAPSS, 623,* 93-107.
Peterson, R. D., and Krivo, L. J. (2010). *Divergent Social Worlds: Neighborhood Crime and the Racial-Spatial Divide*. New York: Russell Sage Foundation.
Peterson, R. D., Krivo, L. J., & Harris, M. A. (2000). Disadvantage and neighborhood violent crime: Do local institutions matter? *Journal of Research in Crime & Delinquency, 37*, 31-63..
Rogers, K. A., & Kelloway, E. K. (1997). Violence at work: Personal and organizational outcomes. *Journal of Occupational Health Psychology*, *2*, 63-71.
Sampson, R. J. (2012). *Great American City: Chicago and the Enduring Neighborhood Effect*. Chicago, IL: University of Chicago Press.
Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology, 94*(4), 774-802.
Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing ‘neighborhood effects’: Social processes & new directions in research. *Annual Review of Sociology, 28*, 443-78.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 277,* 918-924
Sampson, R. J., & Sharkey, P. (2008). Neighborhood selection and the social reproduction of concentrated racial inequality. *Demography, 45*, 1-29.
Schaefer, D. R. (2012). Youth co-offending networks: An investigation of social and spatial effects. *Social Networks, 34*, 141-149.
Singer, S. I. (2014). *America's safest city: Delinquency and modernity in suburbia*. NYU Press.
Shaw, C. R., & McKay, H. D. (1942). *Juvenile Delinquency and Urban Areas*. Chicago: University of Chicago Press.
Small, M. L. (2006). Neighborhood institutions as resource brokers: Childcare centers, interorganizational ties, and resource access among the poor. *Social Problems, 53*, 274-292.
Taylor, Ralph B. (2015). *Community criminology: Fundamentals of spatial and temporal scaling, ecological indicators, and selectivity bias*. NYU Press.
Taylor, S. E., & Repetti, R. L. (1997). Health psychology: What is an unhealthy environment and how does it get under the skin? *Annual Review of Psychology, 48,* 411-447
Thomas, S. A., & Shihadeh, E. S. (2013). Institutional isolation and crime: The mediating effect of disengaged youth on levels of crime. *Social Science Research, 42*, 1167-1179.
Tita, G. E., & Griffiths, E. (2005). Traveling to violence: The case for a mobility-based spatial typology of homicide. *Journal of Research in Crime and Delinquency, 42,* 275–308.
Tran, V. C., Graif, C., Jones, A. D., Small, M. L., & Winship, C. (2013). Participation in context: Neighborhood diversity and organizational involvement in Boston. *City & Community, 12*, 187-210.
Vélez, M. B. (2001). The role of public social control in urban neighborhoods: A multi-level analysis of victimization risk. *Criminology, 39*, 837-864.
Vélez, M. B., Lyons, C. J., & Boursaw, B. (2012). Neighborhood housing investments and violent crime in Seattle, 1981-2007. *Criminology, 50*, 1025-1056.
Vogel, M., & South, S. J. (2016). Spatial dimensions of the effect of neighborhood disadvantage on delinquency. *Criminology, 54*, 434-458.
Wang, H., Kifer, D., Graif, C., & Li, Z. (2016, August). *Crime rate inference with big data.* Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, California.
Wikström, P. O. H., Ceccato, V., Hardie, B., & Treiber, K. (2010). Activity fields and the dynamics of crime. *Journal of Quantitative Criminology, 26*, 55-87.
Wills, A., & Hernandez, S. (2017, Jan 2). 762 murders. 12 months. 1 American city. *CNN*. Retrieved from http://www.cnn.com
Wilson, W. J. (1987). *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy.* Chicago, IL: University of Chicago Press.
Witt, P. A., & Crompton, J. L. (1996). The at-risk youth recreation project. *Journal of Park and Recreation Administration, 14*, 1-9.
Ziersch, A. M. (2005). Health implications of access to social capital: Findings from an Australian study. *Social Science & Medicine 61*, 2119–31.

Table 1. Descriptive Statistics

Variable	Mean	SD	Min	Max	Variable	Mean	SD	Min	Max
Local Crime Variables					Network Crime Variables				
2004-2006 Overall Crime	5899.02	4851.89	431.33	28709.67	2004 Network Overall Crime	8995.06	881.80	7146.09	11876.69
2011-2013 Overall Crime	4285.63	3636.49	326.67	21349.67	2011 Network Overall Crime	6640.02	570.57	5305.91	8539.80
2004 Overall Crime	6066.90	5004.79	402.00	29333.00	2004 Network Violent Crime	2071.57	243.95	1545.67	2975.14
2007 Overall Crime	5658.74	4761.10	416.00	28417.00	2011 Network Violent Crime	1428.34	135.72	1080.15	2053.43
2011 Overall Crime	4556.61	3852.92	368.00	3852.92	2004 Network Property Crime	3465.05	368.01	2802.84	4555.83
2013 Overall Crime	3952.36	3385.69	290.00	20100.00	2011 Network Property Crime	2945.21	294.88	2399.99	3717.99
2004-2006 Violent Crime	1672.80	1542.29	95.67	8755.00	Surrounding Crime Variables				
2011-2013 Violent Crime	1195.79	1117.75	81.33	6357.67	2004 Surrounding Overall Crime	6349.54	3082.83	1238.00	16603.00
2004 Violent Crime	1735.47	1598.77	105.00	9087.00	2011 Surrounding Overall Crime	4767.91	2326.49	1049.75	12550.50
2007 Violent Crime	1600.40	1506.40	103.00	8354.00	2004 Surrounding Violent Crime	1826.06	944.21	237.75	5065.25
2011 Violent Crime	1255.84	1166.84	93.00	6516.00	2011 Surrounding Violent Crime	1323.47	695.98	173.75	3832.50
2013 Violent Crime	1106.18	1040.93	68.00	5971.00	2004 Surrounding Property Crime	1910.88	939.72	446.75	5097.00
					2011 Surrounding Property Crime	1630.54	798.34	368.75	4145.00
2004-2006 Property Crime	1754.51	1354.14	124.00	5831.33					
2004-2006 Property Crime	1460.22	1205.54	104.00	5562.33	Demographic Variables				
2004 Property Crime	1842.39	1454.33	109.00	6376.00	Population Density	5.39	2.81	.43	14.00
2007 Property Crime	1662.44	1326.63	106.00	5889.00	Residential Stability	-.01	.97	-2.11	1.73
2011 Property Crime	1572.64	1281.84	121.00	5510.00	Ethnic Diversity	.00	1.00	-1.30	2.12
2013 Property Crime	1318.48	1099.81	93.00	5260.00	Percent Black	41.20	41.09	.29	98.56
					Percent Hispanic	21.76	25.16	.00	88.91
Network Disadvantage Variables					Internal Disadvantage	-.04	.91	-1.24	2.38
2004 Network Disadvantage	-.42	.17	-.72	-.14					
2011 Network Disadvantage	-.46	.15	-.74	-.14	Surrounding Disadvantage	-.01	.66	-1.02	1.29

NOTE: N=77.

ABBREVIATION: SD = standard deviation.

Table 2. Negative Binomial Regression Predicting 3-Year Spells of Overall Crime

	2004-2006				2007-2009	2010-2012	2011-2013
	M1	**M2**	**M3**	**M4**	**M4**	**M4**	**M4**
Network disadvantage	.455 ***	.248 ***	.208 **	.161 *	.228 ***	.241 ***	.233 ***
	(.059)	(.064)	(.074)	(.068)	(.066)	(.062)	(.068)
Population density		-.311 ***	-.310 ***	-.372 ***	-.370 ***	-.359 ***	-.377 ***
		(.051)	(.050)	(.047)	(.045)	(.044)	(.048)
Residential stability		-.361 ***	-.348 ***	-.255 ***	-.281 ***	-.244 ***	-.270 ***
		(.054)	(.055)	(.060)	(.058)	(.056)	(.059)
Ethnic diversity		-.212 **	-.190 **	-.092	-.105 †	-.102 †	-.086
		(.066)	(.069)	(.066)	(.062)	(.058)	(.065)
Internal Disadvantage		.145 *	.115	.145 *	.125 †	.145 *	.123 †
		(.069)	(.074)	(.067)	(.065)	(.060)	(.067)
Surrounding disadvantage			.089	.036	-.028	-.039	.011
			(.086)	(.074)	(.074)	(.074)	(.079)
Surrounding crime				.134 *	.173 ***	.139 **	.148 **
				(.054)	(.046)	(.044)	(.052)
Network crime				.103	.072	.156 **	.133 *
				(.071)	(.057)	(.053)	(.064)
Intercept	8.481 ***	8.405 ***	8.404 ***	8.391 ***	8.294 ***	8.119 ***	8.066 ***
	(.059)	(.041)	(.040)	(.036)	(.035)	(.034)	(.037)
Dispersion Parameter	3.703	7.872	7.979	9.945	10.672	11.375	9.477
	(.573)	(1.247)	(1.264)	(1.584)	(1.702)	(1.818)	(1.512)
Log Likelihood	-705	-674	-673	-664	-654	-639	-641
AIC	1415	1362	1363	1349	1329	1298	1303

NOTES: N =77. Standard Errors are in parentheses.
†p<.10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

Table 3. Negative Binomial Regression Predicting 3-Year Spells of Crime by Type, 2004-2006 and 2011-2013

	Overall Crime		Violent Crime		Robbery		Homicide		Property Crime	
	2004-06	**2011-13**	**2004-06**	**2011-13**	**2004-06**	**2011-13**	**2004-06**	**2011-13**	**2004-06**	**2011-13**
Network disadvantage	.162 *	.233 ***	.217 **	.238 ***	.291 **	.278 *	.347 **	.481 ***	.237 ***	.280 ***
	(.068)	(.068)	(.080)	(.070)	(.106)	(.110)	(.124)	(.128)	(.070)	(.074)
Population density	-.365 ***	-.376 ***	-.226 ***	-.218 ***	-.133 †	-.172 †	-.072	-.059	-.436 ***	-.424 ***
	(.050)	(.051)	(.053)	(.054)	(.075)	(.089)	(.095)	(.106)	(.050)	(.049)
Residential stability	-.260 ***	-.272 ***	-.204 ***	-.205 ***	-.203 **	-.172 †	-.030	-.045	-.258 ***	-.230 ***
	(.061)	(.060)	(.057)	(.057)	(.077)	(.094)	(.088)	(.095)	(.065)	(.066)
Ethnic diversity	-.100	-.087	-.123 †	-.092	-.072	-.032	-.069	.025	.004	-.006
	(.069)	(.068)	(.066)	(.065)	(.089)	(.107)	(.101)	(.102)	(.076)	(.072)
Internal Disadvantage	.149 *	.124 †	.303 ***	.277 ***	.147	.156	.355 ***	.388 ***	-.050	-.005
	(.068)	(.067)	(.072)	(.069)	(.093)	(.108)	(.101)	(.100)	(.067)	(.069)
Surrounding disadvantage	.032	.010	.058	.065	.196 †	.184	.099	.070	.081	.037
	(.074)	(.079)	(.077)	(.078)	(.103)	(.129)	(.119)	(.118)	(.074)	(.079)
Surrounding crime	.143 *	.150 **	.152 *	.154 *	.240 **	.139	.114	.166 *	.194 ***	.187 ***
	(.059)	(.057)	(.064)	(.064)	(.089)	(.103)	(.082)	(.074)	(.057)	(.056)
Network crime	.098	.132 *	.016	.059	.028	.269 *	.024	.090	.170 *	.220 **
	(.073)	(.065)	(.078)	(.067)	(.100)	(.117)	(.082)	(.109)	(.074)	(.070)
Temporal lag	-.019	-.005	-.046	-.045	-.025	.005	.037	.017	-.036	-.004
	(.049)	(.050)	(.052)	(.053)	(.069)	(.084)	(.045)	(.048)	(.054)	(.056)
Intercept	8.391 ***	8.066 ***	7.056 ***	6.720 ***	4.925 ***	4.706 ***	1.209 ***	1.137 ***	7.202 ***	7.007 ***
	(.036)	(.037)	(.037)	(.037)	(.049)	(.059)	(.067)	(.070)	(.035)	(.037)
Dispersion Parameter	9.96	9.48	9.62	9.59	5.73	4.05	403.43	403.43	10.58	9.77
	(1.59)	(1.51)	(1.55)	(1.56)	(1.00)	(.70)	(.55)	(.65)	(1.71)	(1.58)
Log Likelihood	-664	-641	-563	-538	-420	-415	-142	-138	-571	-559
AIC	1351	1305	1149	1098	863	852	306	298	1165	1141

NOTES: N =77. Standard Errors in parentheses.
†p<.10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

Table 4. Leave-One-Out Cross-Validation: Comparing Model Performance in Predicting 3-Year Spells of Crime by Type

		2004-2006			2007-2009			2010-2012			2011-2013		
		Overall Crime	**Violent Crime**	**Property Crime**	**Overall Crime**	**Violent Crime**	**Property Crime**	**Overall Crime**	**Violent Crime**	**Property Crime**	**Overall Crime**	**Violent Crime**	**Property Crime**
M1	MAE	1744.960	457.203	588.396	1572.869	414.415	555.406	1338.676	350.827	513.403	1319.130	329.759	493.407
	MRE	.371	.394	.402	.386	.408	.414	.384	.407	.420	.399	.406	.425
	AIC	1373.400	1170.500	1201.400	1361.100	1159.100	1189.300	1339.100	1134.400	1185.500	1333.300	1125.300	1178.300
M2	MAE	1688.182	453.927	568.394	1470.978	404.259	507.919	1249.469	335.313	504.002	1211.069	315.943	488.528
	MRE	.322	.345	.319	.327	.346	.322	.321	.342	.329	.333	.344	.337
	AIC	1353.700	1154.000	1170.800	1340.500	1137.800	1157.400	1316.500	1113.900	1154.200	1311.300	1106.400	1149.900
M3	MAE	1796.719	499.896	595.206	1529.527	402.851	532.931	1314.210	348.769	527.758	1233.421	338.482	508.491
	MRE	.314	.340	.319	.315	.321	.322	.303	.310	.321	.328	.339	.340
	AIC	1352.400	1152.000	1171.500	1338.000	1128.200	1158.000	1309.500	1102.800	1149.700	1311.400	1104.900	1149.800
M4	MAE	1759.377	474.540	591.245	1537.967	402.368	535.394	1295.765	335.162	539.952	1243.160	313.497	518.020
	MRE	.318	.345	.322	.316	.322	.324	.300	.309	.321	.333	.340	.342
	AIC	1354.300	1153.700	1173.300	1339.800	1129.900	1160.000	1311.200	1104.800	1151.600	1313.400	1106.600	1151.800
M5	MAE	1753.112	**451.368**	**543.626**	1509.161	**390.973**	**474.996**	1271.008	**332.218**	504.750	**1192.723**	**298.101**	**458.074**
	MRE	.315	**.336**	**.302**	**.304**	**.315**	**.300**	**.287**	**.309**	**.311**	**.305**	**.315**	**.310**
	AIC	**1350.800**	**1148.700**	**1164.500**	**1330.600**	**1122.100**	**1145.600**	**1299.500**	**1097.500**	**1140.600**	**1304.500**	**1097.800**	**1140.600**

NOTES: N=77. Bolded values indicate the models in which including network disadvantage (M5) produces the lowest error.
M1 includes demographic predictors (population density, residential stability, ethnic diversity, and internal disadvantage). M2 includes all variables in M1, surrounding disadvantage, and surrounding crime. M3 includes all variables in M2 and network crime. M4 includes all variables in M3 and temporal lag. M5 includes all variables in M4 and network disadvantage.

Table 5. Permutation Tests on 3-Year Spells of Crime by Type for 2004-2006 and 2011-2013 (1000 Permutations)

	2004-2006			2011-2013		
	Overall Crime	Violent Crime	Property Crime	Overall Crime	Violent Crime	Property Crime
Network disadvantage	.162	.217 **	.237 **	.232 *	.238 *	.279 **
	(.178)	(.007)	(.008)	(.035)	(.012)	(.006)
Population density	-.364 ***	-.226 **	-.435 ***	-.375 ***	-.217 **	-.423 ***
	(.000)	(.008)	(.000)	(.000)	(.002)	(.000)
Residential stability	-.260 ***	-.203 †	-.258 ***	-.272 **	-.203 *	-.231 ***
	(.000)	(.056)	(.000)	(.002)	(.025)	(.000)
Ethnic diversity	-.101 †	-.123 †	.003	-.088 †	-.092 *	-.007
	(.095)	(.095)	(.872)	(.091)	(.029)	(.814)
Internal Disadvantage	.151	.306 ***	-.049	.126	.280 **	-.004
	(.807)	(.000)	(.377)	(.416)	(.001)	(.564)
Surrounding disadvantage	.031	.056	.080	.010	.063	.038
	(.909)	(.893)	(.975)	(.939)	(.862)	(.980)
Surrounding crime	.144	.151	.193 *	.150	.153	.187 *
	(.849)	(.809)	(.010)	(.689)	(.497)	(.012)
Network crime	.096	.016	.168	.130	.059	.217
	(.998)	(.984)	(.995)	(.927)	(.962)	(.935)
Temporal Lag	-.019	-.045 †	-.035 †	-.004	-.045 *	-.003
	(.413)	(.066)	(.075)	(.558)	(.014)	(.253)
Intercept	8.391 ***	7.056 ***	7.202 ***	8.066 ***	6.719 ***	7.007 ***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)

NOTES: N=77. P values in parentheses.
†p<.10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).