Population Distribution, Neighborhood Networks, and Neighborhood Crime: A Simulation Study

John R. Hipp*
Carter T. Butts
Ryan Acton
Nicholas N. Nagle
Adam Boessen

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* Department of Criminology, Law and Society and Department of Sociology, University of California, Irvine. Address correspondence to John R. Hipp, Department of Criminology, Law and Society, University of California, Irvine, 3311 Social Ecology II, Irvine, CA 92697; email: john.hipp@UCI.edu. This research is supported in part by NSF grant BCS-0827027

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Abstract

We propose taking networks seriously into account when assessing their effect on neighborhood crime rates. We do this by first spatially locating the households of a city into their constituent blocks. Then, employing spatial interaction functions based on prior empirical work (and the implicit effect of residential mobility on the spatial distribution of personal network ties), we simulate a network of ties among these residents. Based on this simulated network, we compute network statistics that more appropriately capture the notions of cohesion and information diffusion that underlie theories of networks and crime. We then show the robustness of this approach for predicting levels of crime at the very micro geographic level of blocks on five separate cities. We conclude by considering extensions of the approach that account for homophily, as well as propinquity, in the formation of network ties.

Keywords: neighborhoods, crime, social networks, spatial effects, simulation

Bio

John R. Hipp is an Associate Professor in the department of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis. He has published substantive work in such journals as *American Sociological Review, Criminology, Social Forces*, *Social Problems, Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology*, *Psychological Methods*, and *Structural Equation Modeling*.

Carter T. Butts is an Associate Professor in the department of Sociology at the University of California, Irvine.

Nicholas N. Nagle is an Assistant Professor in the department of Geography at the University of Tennesse.

Ryan Acton is an Assistant Professor in the department of Sociology at the University of Massachusetts, Amherst.

Adam Boessen is a doctoral student in the Department of Criminology, Law and Society at the University of California - Irvine. His primary research interests include the community of context of crime, spatial analysis, social network analysis, and juvenile delinquency. His work uses quantitative methodologies to examine the relation between residential mobility and crime, the measurement and conceptualization of neighborhoods, and the impact of incarceration on juvenile offenders.

Population Distribution, Neighborhood Networks, and Neighborhood Crime: A Simulation Study

A recurrent theme in the ecological study of crime is the theorized importance of social networks among residents for the reduction of crime. One particularly prominent theory in this regard is social disorganization theory, which posits that structural characteristics such as racial/ethnic heterogeneity and residential instability affect the formation of social ties, and that these ties enable residents to engage in informal social control to reduce the amount of crime in the neighborhood (Bursik 1988; Sampson and Groves 1989; Shaw and McKay 1942). Thus, these network ties are posited to lead to neighborhood cohesion, which may enhance the perception of neighborhood collective efficacy towards providing informal social control in response to deviant behavior (Sampson 2006).

Despite the continued presence of social networks in theories about the ecology of crime, it is striking that this theorizing is still at an infant stage. In understanding the role of social networks, little consideration is given to the appropriate network structural characteristics that should be important to measure. Despite the rich discussion in the social network literature describing the important consequences of various structural characteristics for fostering information flow and cohesion—two phenomena that are arguably quite important in various criminological theories of neighborhood crime—criminological theory generally fails to exploit the large body of knowledge in this area.

The present study addresses this limitation. Recognizing that the existing literature almost exclusively utilizes one social network measure (density) in studying the effect of networks on crime rates—and we will point out that even this measure is usually only implicit in the theorizing of such studies—we will construct several social network measures that are motivated by criminological theory on the important role networks are expected to play in neighborhoods, as well as social network theory on which network structural characteristics are expected to enhance such an outcome. Furthermore, given that prior criminological theory has only peripherally considered the role of propinquity for social tie formation (and therefore has underappreciated its importance), in this study we will focus explicitly on the role of spatial distance for tie formation. The lack of available empirical data regarding these questions—given that it requires information on the social network ties of all residents of a city—is addressed in the present study with a novel approach: we *simulate* networks. Although our approach may appear somewhat unconventional at first glance, we argue below that numerous prior studies in the neighborhoods and crime literature have implicitly used a very simple "simulation" model of social tie choice, and then considered only the network measure of density in testing the effect on crime rates. Although simplified, our simulations are extrapolated from interaction and population data, and thus plausibly reflect the general contours of real urban networks. As we show, even this very broad approximation is sufficiently powerful to provide robust results for crime event prediction in five US cities.

Crime in neighborhoods

The role of social ties in reducing crime

Although there are several key ecological theories of crime, each positing various mechanisms through which neighborhood demographics affect criminal behavior, a common theme running through many of these theories is the posited role of the network of social ties among residents. *Social disorganization theory* is most prominent in this regard, positing that structural characteristics such as racial/ethnic heterogeneity and residential instability affect the formation of social ties, and that these ties in turn enable residents to employ informal social control to reduce the amount of crime in the neighborhood (Bursik 1988; Sampson and Groves 1989; Shaw and McKay 1942). From a social network perspective, this is not a particularly sophisticated theory in terms of the effect of network structure, given that it simply posits that the mere presence of more social ties on average for the residents of a neighborhood (what is referred to as *mean degree* in network terminology) will in and of itself increase informal social control. The importance of resident social networks was further elaborated by Sampson (2006), who argued that social ties among residents are a necessary precondition for the formation of *collective efficacy* in neighborhoods, which also impacts crime rates. Again, in his formulation, the specific structural network characteristics that might be important in fostering collective efficacy are not elaborated, and instead mean degree is generally implicit.

To move criminological theorizing forward in thinking about the role of social networks among residents, we feel it is useful to begin with the question of *why* social ties might reduce the amount of crime in neighborhoods. We suggest that there are at least two mechanisms through which they might operate: 1) by increasing cohesion (both within the neighborhood, and across neighborhoods); 2) by transmitting information. We consider each of these in turn.

First, the presence of positive social ties will likely increase the level of perceived cohesion in a neighborhood. Scholars posit that a greater sense of cohesion within a collectivity will increase residents' willingness to engage in crime-inhibiting behavior such as providing informal social control (Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997). Scholars in the social network literature have developed a number of structural measures intended to capture the degree of cohesion within a particular network, or a subgroup of a larger network. One set of measures is based upon the principle of the number of ties among members of a group. Thus, some scholars have posited that the average number of ties by members of the network or group (mean degree) is a measure of cohesion (Wasserman and Faust 1994).[1] Other scholars have argued that the density of ties is a better measure of cohesion: that is, the proportion of ties that exist out of all possible ties that might exist (Blau 1977)(Lakon, Godette, and Hipp 2007). This measure changes the denominator from population (for mean degree) to, essentially, population squared. Thus, this captures not the number of ties per person, but rather the proportion of all possible ties.

Another common principle contained in many cohesion measures is the notion of the ratio of within-group ties to out-group ties. Thus, network scholars frequently measure the cohesion of a subgroup based on the degree to which social ties are within group rather than across group (e.g. the LS sets of Luccio and Sami 1969). While network researchers frequently consider endogenous notions of "group" in this regard, this same principle of internal versus external contact can also be applied to groups induced by exogenous characteristics (such as membership in a physical neighborhood). For instance, Krackhardt and Stern (1988) introduce a measure of cohesion known as the E-I index, which measures the extent to which ties associated with a pre-defined group are concentrated on in-group versus out-group members. By measuring the "inwardness" versus "outwardness" of a group's ties, Krackhardt and Stern were able to predict differences in the performance of organizational units subjected to adverse conditions. Under strain, highly inward-focused groups rallied internally, but were unable to cooperate with others to advance their collective interest; by contrast, more outwardly focused groups were better able to sustain cooperation with other units, and to thereby regain lost performance.

In a neighborhood context, such effects may imply a two-sided element to the effects of

[1] Moody and White (2003) created a measure that explicitly defined cohesion based on the notion of the vulnerability of the group to the removal of one or a few of the actors.

cohesion: when effective crime control depends primarily on internal coordination, neighborhoods whose residents are tied primarily to fellow residents may be at an advantage. That is, neighborhoods better able to provide parochial control, as termed by Hunter (Hunter 1995; Taylor 1997), would be captured by this measure. When, however, crime control requires the mobilization of resources that lie outside the neighborhood itself (e.g., political action, influence over the policing process, coordination with other neighborhoods)—that is, what Hunter (Gans 1962; Hunter 1995) referred to as public control--this form of cohesion may be a liability rather than an asset.

If the ability to garner public control is important, a measure capturing the linkage of ties into the broader community is important. A network measure that arguably captures such cohesion with the larger community is the average *k*-core (Seidman 1983) number. *k*-cores are defined as sets of vertices such that every member of the set is adjacent to at least k other members of the set. An important property of *k*-cores is that they are locally cohesive: although cores need not be connected, every member of a high-order core belongs to a locally cohesive set. For $k>1$, these sets necessarily contain spanning cycles, and are thus robust to the loss of edge or vertices. Those belonging to high-order cores have a dramatically enhanced chance of being able to reach some local set of individuals relative to those belonging to low-order cores. The average core number in a given population thus serves as a natural proxy of the extent to which members of the population are typically part of such robustly connected subgroups.

Second, networks can transmit information between residents. Information regarding criminal activity is a necessary precondition for residents to get involved in improving the neighborhood: clearly, residents must be aware of neighborhood problems in order to mobilize to address them. Not only does information about problems flow through interpersonal networks, but so too does information about fellow residents' willingness to engage in problem-solving behavior. The sense of collective efficacy derived from the knowledge that one's fellows are willing and able to act towards the common interest is arguably necessary to encourage residents to engage in behavior that otherwise may not benefit themselves directly (Sampson, Raudenbush, and Earls 1997). As Sampson (2006) has argued, social relations among residents are a necessary precondition for the formation of collective efficacy.

There are various measures that capture the potential of a network to transmit information in the most efficient manner. One way to think about measuring information flow is to build on the insights of literature measuring diffusion potential (Moody 2002; Valente and Davis 1999). In this perspective, it is important to assess the potential for information to flow throughout the network. In some network structures, information can flow easily to a large number of persons. On the other hand, some network structures inhibit the flow of information across groups, instead constraining it within particular subgroups. For example, Butts (2010) measured this using the notion of the average size of the component to which each resident in the neighborhood belongs. Specifically, Butts investigated the maximum number of persons who could be reached by a signal introduced to a randomly selected individual in the network; the expectation of this maximum is a natural measure of the *diffusion potential* of a network, with higher values indicating networks in which, on average, more members can be reached by randomly arriving information or resources.

How do criminologists model social tie formation?

Criminological theory generally adopts a rather impoverished theoretical model of tie formation. The notion of homophily—that is, the preference to form ties with others who are similar to oneself—is pervasive in the social network literature (for a nice review, see

McPherson, Smith-Lovin, and Cook 2001). Homophily can be induced by various social statuses, including race/ethnicity, economic resources, marital status, religious affiliation, the presence of children, etc. When considering the role of homophily, criminological theory almost exclusively focuses on the importance of homophily based on race/ethnicity (Sampson and Groves 1989; Veysey and Messner 1999). Scholars frequently point to the social disorganization theory when positing that racial/ethnic heterogeneity will reduce tie formation, rather than referring to the more general principle of social distance. In practice, researchers tend to simply include a measure of racial/ethnic heterogeneity in the neighborhood and test whether it affects the crime rate, with the implicit, or sometimes explicit, mechanism being these social ties (Hipp 2007b; Roncek and Maier 1991; Sampson and Groves 1989; Warner and Rountree 1997). A consequence of ignoring the more general principle of social distance is that studies rarely consider other social dimensions beyond race/ethnicity. An exception is a recent study considering the social distance engendered by economic inequality (Hipp 2007b), and a few studies testing whether the presence of economic inequality in neighborhoods is associated with higher crime rates (Crutchfield 1989; Hipp 2007b; Messner and Tardiff 1986). Another exception is a study measuring social distance along a number of dimensions for the residents in a micro-neighborhood, and assessing the effect of this social distance on collective perceptions of disorder and crime (Hipp 2010).

Although studies testing the effect of racial/ethnic heterogeneity on crime rates simply describe their theoretical expectations in a discursive manner, we can consider the process a little more explicitly. First, such studies posit that homophily tendencies combined with racial/ethnic homogeneity in a neighborhood increases the number of social ties among residents (*mean degree* in social network terminology), which then results in more crime reduction behavior and hence less crime.[2] This implies a model in which the only thing driving tie choice is homophily based on the race/ethnicity of residents. That is, two residents are hypothesized to be more likely to form a tie if they share the same race/ethnicity. Therefore, if the outcome measure (Y) represents either the presence (1) or absence (0) of a tie, then it is natural to treat the association via a standard logistic form, i.e.

$P(Y=1) = [1+\exp(-XB)]^{-1}$

where X only contains information on the difference in race/ethnicity of all possible dyads in a neighborhood (and allows for any transformations of X) and B is the parameter capturing the hypothesized effect on tie formation. In principle, researchers could simulate the presence of social ties based on such a model, compute various possible network measures based on the information from this simulation, and include them as covariates in a model predicting the amount of crime in a neighborhood. Given the simplicity of this tie choice model, researchers in practice do not in fact perform such simulations, but simply include a measure of racial/ethnic heterogeneity as a proxy for mean degree.

Criminological theories also do not incorporate propinquity into their tie choice models in a very sophisticated fashion. In fact, the only nod to the importance of propinquity can be seen in the social disorganization theory (Sampson and Groves 1989) and systemic theory (Kasarda and Janowitz 1974) hypotheses that residential stability in a neighborhood increases the number of social ties. Propinquity is implicitly present in these theories: the hypothesized process is one in which shared time living in the same neighborhood will increase the likelihood of a tie forming, or that formed ties will develop into stronger ties. Thus, studies have tested whether longer residence in a neighborhood will increase the number of ties one will have to fellow

[2] This is not density of ties, because it does not simultaneously take into account population size. That is, if density of ties were important, it would be necessary to account for both racial/ethnic heterogeneity as well as the population size squared (given that this is the denominator of the density of ties measure).

residents, or a contextual effect in which higher overall neighborhood residential stability has an additional effect on tie formation beyond the individual effect for households. In this tie choice model, X now represents the shared time in the neighborhood for each dyad in the neighborhood. The social network of the neighborhood could be simulated based on this simple model, though again, researchers in practice do not in fact perform such simulations, but instead simply include a measure of neighborhood residential stability in the model predicting crime (Bellair 2000; McNulty and Holloway 2000; Warner and Pierce 1993).

On the other hand, a small but growing body of research in the social networks literature has developed a more sophisticated view of the role of propinquity by focusing on the spatial distribution of the social ties of residents. This literature has suggested that spatial proximity is important for fostering tie formation and this effect can be captured by a distance decay function. This propinquity effect was demonstrated in two early studies focusing on the formation of ties in micro-areas (Caplow and Forman 1950; Festinger, Schachter, and Back 1950), as well as a more recent study (Hipp and Perrin 2009). These studies showed that ties were more likely to form to others who lived closer within the same housing complex. Although these studies have focused on the network of ties among residents in relatively small geographic areas that are the size of neighborhoods or smaller, scholars have generalized these ideas to the notion of positing and estimating the proper distance decay function to capture this spatial distribution of ties (Butts Forthcoming).

In part, the spatial distribution of ties is due to the propinquity effect of tie formation. However, another important process that contributes to the spatial distribution of ties is residential mobility. Residential mobility can put a strain on ties: as a consequence of mobility by a household, some ties will be severed or fade away. Another consequence is that the ties that are not broken by such mobility will subsequently span a larger physical distance. This may have important implications for crime rates if indeed networks impact residents' ability to combat crime in their neighborhoods. A large literature in demography has focused on the spatial component of residential mobility. Scholars have studied the relative likelihood of residential mobility within a particular community compared to migration to a different metropolitan area (Clark and Ledwith 2006; Quigley and Weinberg 1977; Sandefur 1985). The evidence consistently shows a spatial distance decay function for the distance of moves, which we point out will then impact the spatial distribution of existing ties.

Note that the existing approaches in the criminological litearture implicitly focus on the role of mean degree as the measure of network structure. Although researchers generally do not articulate it in this manner, this in fact is what is done. Indeed, a common measure for "directly" measuring the networks of residents is to ask respondents about how many neighbors they know, and then to compute the mean among residents in the neighborhood (which is, explicitly, mean degree). We argue that there is little reason to suspect that mean degree is the only, or even the most appropriate, possible network measure that would be of importance for neighborhood crime rates. As we discussed earlier, other network structural measures are likely even more appropriate. We suggest that the lack of empirical data on complete networks among residents in cities is what has held back theorizing in this regard.

Our approach here differs from previous studies in three manners. First, we develop a model of tie choice based on the spatial distance between residents based on the insight that social ties are inhibited by spatial distance between residents. This insight comes from the geography literature (see, e.g., Tobler 1970), and we estimate a tie choice model that explicitly incorporates the notion of a distance decay. Second, we simulate the social ties expected based on this model, by using the actual geography of the households in the five cities in our study. Note that we could build a more sophisticated model of tie choice that incorporated information on residential mobility of residents, as well as social distance among them based on characteristics such as race/ethnicity, income, or household type. However, we leave these additional complications to future work as our intention here is to simply illustrate the importance of incorporating geographic distance between residents given that criminology scholars have generally overlooked it. Furthermore, there is surprisingly little empirical evidence regarding the actual parameters that would be appropriate to capture the effect of social distance on neighborhood ties, which also limits the utility of presently attempting to incorporate such information into a simulation. Nonetheless, we highlight that recent work by Butts (2010) has shown that models based on distance effects alone can be quite robust to omitted tie formation mechanisms such as triad closure bias, even for complex phenomena such as diffusion potential. Third, we then compute several social network measures from these simulated networks. We therefore do not simply compute the mean degree of implied ties in a neighborhood, but instead employ several additional theoretically informed social network measures that address the issues of cohesion and information flow that we identified above.

Data and Methods

Data

Our study focuses on five cities for which we have data on the actual occurrence of reported crime events ("point data"). This allows us to place crime events into the very small geographic container of blocks to capture possible micro-geography effects (Hipp 2007a; Weisburd, Bernasco, and Bruinsma 2009). These cities are Buffalo, Cincinnati, Cleveland, Sacramento, and Tucson. We combine census data information on the location of households in the blocks of these cities, along with GIS techniques to locate these blocks across the geography of the cities. The Census data provides information on the number of households in a block, along with the number of persons in each household (with a limitation that the upper bound category contains households of 9 or more persons, inducing a degree of uncertainty regarding the number of persons in these units).

With this information on the number of households in a block we generate points for these households based on two different assumptions (since we do not have information on the actual location of the housing units). Under the first model, we assume a uniform micro-distribution; this implies a maximum entropy solution in which households are placed uniformly at random in the block. Under the second model, we assume a quasi-random micro-distribution; this implies a near-minimal entropy solution, in which households are placed in an extremely even manner using a low-discrepancy sequence (specifically, a two-dimensional Halton sequence). Given that the general pattern of results were similar using both of these point placement patterns, for brevity we present only those from the quasi-random distribution.

To then simulate the social networks, we need to employ a particular spatial interaction function (SIF) to model the geographic distribution of ties. The research in this area is sparse, making it difficult to know the functional form of the spatial effect of distance on tie formation. We therefore tested two SIF's that were obtained in prior research. The first we refer to as the "Festinger" SIF, as it is based on the Festinger, Schachter, and Back (1950) study in 1950 viewing the spatial distribution of a social friendship relation. This function is locally somewhat sparse, with a fairly long tail. The second SIF we refer to as the "Freeman" SIF, as it is based on the Freeman et al. (1988) study of a face-to-face interaction relation. The function is a locally dense relation that attenuates very quickly with distance. Both are of the general power law form, with the Festinger SIF declining approximately with d raised to -2.8, and the Freeman SIF declining approximately with d raised to -6.4. Given that the general pattern of results were similar using both of these SIF's, for brevity we present only those from the Festinger SIF.

Dependent variables

Our outcome variables are measures of violent crime and property crime. We combine aggravated assaults, robberies, and homicides into the measure of violent crime. We combine burglaries, motor vehicle thefts, and larcenies into the property crime measure. We estimated ancillary models with these crime types disaggregated and the pattern of results was similar to that presented here for these two aggregated measures. We therefore only present the violent and property crime models.

Independent variables

We included several network population distribution measures intended to capture the theoretical ideas described above. We included three social network measures intended to capture cohesion within the neighborhood. First, following prior research, we include mean degree. This is simply the average number of social ties for persons in the neighborhood. Second, we include a measure of tie density, given that this is frequently used as a measure of cohesion (Wasserman and Faust 1994). This measure divides the number of social ties in the neighborhood by the number of possible ties (which is $p(p-1)/2$, where p = population). The third measure captures the extent to which ties are inward-focused: the proportion of ties that are within the geographic unit (measured at three geographic units: within the block, within the block group, and within the tract). Larger values indicate a higher proportion of ties within the geographic unit.

We also created a measure to capture cohesion not bounded within the neighborhood. This measure is the average of k^i within the neighborhood, where k^i is the order of the highest *k*-core to which the *i*th resident in the neighborhood belongs.[3] A resident with a high core number belongs to relatively well-connected sets, while those with low core numbers belong to subgroups that are easily divided by the removal of nodes or edges; thus larger values for this measure indicate that residents are well-connected in the entire network of the city. Note that these *k*-cores are not constrained to the local neighborhood, but might also reach out into the broader community.

We created a measure of diffusion potential that likely captures a network structure that enhances the transmission of information. This measure was suggested by Butts (2010), and it captures the average size of the component to which each resident in the neighborhood belongs. This is measured as the maximum number of persons who could be reached by a signal introduced to an individual in the network; the expectation of this maximum is a natural measure of the *diffusion potential* of a network, with higher values indicating networks in which, on average, more members can be reached by randomly arriving information or resources.

To minimize the possibility of obtaining spurious results, we included several demographic measures that are commonly included as predictors of crime rates in neighborhoods. This first set of variables was included in models at all three geographic units of analysis. We take into account the racial/ethnic composition with measures of the percent African American and Latino. We also account for racial/ethnic heterogeneity with a measure of the Herfindahl index of five racial/ethnic groupings (white, African American, Latino, Asian, and other race), which takes the following form:

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[3] A *k*-core is a maximal group of actors in which all are tied to at least *k* other actors in the core. Larger values of *k* imply smaller groups, but with more connections.

(1) $$H = 1 - \sum_{j=1}^{J} G_j^{\ 2}$$

where G represents the proportion of the population of ethnic group *j* out of *J* ethnic groups. To account for the presence of vacant units that might increase crime, we included a variable of the percent occupied units in the neighborhood. Given that homeowners may be more invested in the neighborhood and therefore engage in more crime fighting behavior, we included a measure of the percentage of units that are owned. Given that single parent households are often included in an index of concentrated disadvantage, for the block-level models we constructed a measure of the percent single parent households (since this is the only measure of "disadvantage" we have for blocks).

In the models for block groups and tracts, we were able to account for measures that are not available at the block level. Specifically, instead of the single parent household measure, we created a measure of concentrated disadvantage by combining four variables through principal components analysis: median household income, percent at or below 125% of the poverty level, percent single parent households, and the unemployment rate. We also included measures of income inequality in the neighborhood (based on the Gini coefficient).

Table 1 displays the summary statistics for the five cities broken out for the three geographic units of analysis---blocks, block groups and tracts.[4] As can be seen, the cities range in population density from those of the older, denser cities in the east of Buffalo, Cincinnati, and Cleveland, to the newer, more sprawling cities of the west in Sacramento and Tucson. Tucson is a particularly sprawling city. We see that mean degree is highest in Buffalo and Cleveland, and

[4] Although we only display the results from the Festinger SIF using the quasi-random point placement, we briefly note that in the summary statistics, the "Festinger" SIF yields much larger personal networks than does the "Freeman" SIF, which is by design. The strong decay of the Freeman SIF results in much fewer social ties. On the other hand, the difference between using the quasi versus the uniform placement of household points has a much smaller impact on the size of these networks.

lowest in Tucson. However, diffusion potential follows a different pattern, as it is highest in Cleveland and Tucson, but lowest in Cincinnati. When viewing the proportion of ties within a geographic unit, the values are highest in the two low density cities (Sacramento and Tucson) and lowest in Cleveland. Thus, we can see that, in line with insights from urban sociologists, the idiosyncratic features of each urban environment are expected to produce regional network structures with rather different properties.

<<<Table 1 about here>>>

Methods

Given that our outcome variables are counts, we estimated negative binomial regression models (allowing us to account for overdispersion in these counts). To account for the varying size of the geographic units, we include the logged population size as an offset variable with a coefficient constrained to 1; this effectively transforms our outcome into a crime rate measure.

It is important to take into account the possibility that effects may differ based on the level of aggregation for ecological studies of crime (Hipp 2007a). We therefore estimated models from our five cities for three geographic units of analysis: blocks, block groups, and tracts. We treated the cities as five independent tests of our network measures, and estimated separate models for each of the cities to test the robustness of the findings. For all models, we included all of the control variables described above. We first adopted a strategy of including our various network variables one at a time in models. Given the mathematical overlap that exists for some of these measures, it is important to carefully consider which variables are simultaneously included in a model. After these initial models with these measures included separately, we estimated a model for each city that included several of the network measures simultaneously. For all models, we only show the results using the quasi Festinger SIF and quasi-random point placement (given that the results tend to be similar over these four combinations). We in turn explore the effects of these network measures when measured at the level of: 1) blocks, 2) block groups, and 3) tracts.

Results

Turning first to the results for our network measures of cohesion, we see that they show quite robust results. For mean degree—the measure that is most frequently used by criminologists, even if they do not explicitly define it as such—we see in model 1 in Table 2 that this measure generally does a quite good job explaining the location of crime when using the block aggregation. In four of the five cities, blocks with higher mean degree have much lower violent crime rates, with the only exception being in Cincinnati. Thus, a one standard deviation increase in the mean degree within a block reduces the violent crime rate from 19.9% in Buffalo to 38.3% in Tucson. This effect of mean degree is robust over all five cities in the property crime models in specification 1 in Table 3, reducing property crime across these cities between 10.3% and 39% for a one standard deviation increase in mean degree.

<<<Tables 2 and 3 about here>>>

However, there is little evidence that tie density lowers crime levels, despite its importance in other social network contexts. At the block level, tie density actually is associated with *higher* levels of violent and property crime across most of these cities (specification 2 in Table 2). Thus, whereas when computing the number of ties as a proportion of persons (mean degree) shows evidence of lowering property and violent crime rates, computing them as a proportion of possible ties (tie density) results in higher property and violent crime rates. This seeming paradox can be resolved if we bear in mind that mean degree must increase with population size in order for density to be maintained: if mean degree is roughly fixed, increasing population will force density to decline. Under the spatial model, increasing population proportionately with the same geographical distribution maintains approximate density (instead increasing mean degree). We thus infer from the above pattern that it is the geographic *concentration* of population that is more conducive to crime, holding constant the number of ties per person. Ties can be a resource for collective efficacy, but they must compete against the increasing opportunities for predation that arise within large, closely packed populations.

Arguably, the strongest effects are seen for the measures capturing the proportion of ties within the local unit. In specification 3 in Table 2, we see that in blocks in which resident ties are disproportionately to others in the same block there are much lower levels of violent crime, even when controlling for the typical measures included in ecological analyses of crime. A one standard deviation increase in the proportion of ties within-block decreases the violent crime rate from 13% in Sacramento to 39.3% in Cincinnati. The effects are equally strong if we compute the tendency for inward ties among block members but instead define the “in-group” to be either other residents in the same block group or tract (specifications 4 and 5). For the models in Table 3 with property crime as the outcome, we also see a strong protective effect on crime rates when a higher proportion of ties are within-block. A one standard deviation increase in the proportion of ties within-block decreases the property crime rate from 5% in Sacramento to 28.1% in Cincinnati (specification 3). When defining in-group ties based on the block group or the tract as the unit, we see that a higher proportion of such ties reduce property crime rates (specifications 4 and 5). Note that these findings for the importance of within-area ties are contrary to some evidence found by Bellair (2000), who used a measure of reported ego networks of residents.

Turning to our measure capturing cohesion not bounded by the block, we see in four of the five cities studied here that higher values on the *k*-core measure (showing more robust local connectivity) are associated with lower violent crime rates (specification 6 in Table 2). A one standard deviation increase in the measure is associated with from 16.6% less violent crime in Buffalo to 33% less violent crime in Sacramento and Tucson. However, higher values on the *k*-core measure are actually associated with higher violent crime rates in Cincinnati. The results in the property crime models in specification 6 in Table 3 for the *k*-Core measure demonstrate an even more uniform pattern in which higher values for this measure are associated with lower property crime rates in all five cities.

The pattern of the effect for the diffusion potential variable—meant to capture information flow—is much more ambivalent for predicting the location of crime when measured at the block level. The diffusion potential variable shows a significant negative effect in two cities and a significant positive effect in one in the violent crime models (specification 7 in Table 2). It also shows mixed results in the property crime models (specification 7 in Table 3), suggesting that it is not a useful proxy for capturing information flows that might reduce crime rates.

Aggregating network measures to block groups

We next tested whether these network measures show similar effects when aggregated to the larger geographic unit of block groups rather than blocks. As seen in Table 4, the measures of cohesion still are significant predictors of violent crime rates, although the effects are somewhat weaker. We see in specification 1 that mean degree, when measured at the block group level, is associated with lower violent and property crime rates in four of these five cities (Cincinnati is the one exception). A one standard deviation increase in mean degree in the block group is associated with a 5.6% decrease in violent crime in Cleveland to a 17.6% decrease in Tucson. The effects of mean degree on property crime rates in Table 5 are even stronger.

<<<Tables 4 and 5 about here<<<

Tie density again shows very mixed results for both violent and property crime rates in specification 2 in Tables 4 and 5.

The measure of cohesion based on the proportion of within-group ties again exhibits a negative relationship with violent crime rates: a one standard deviation increase in the proportion of ties within the same block group reduces the violent crime rate from 7.2% in Cleveland to 24.4% in Tucson in specification 4 in Table 4. Furthermore, the clustering of ties within the blocks contained within the block group also reduces the violent crime rate (specification 3 in Table 4), as a one standard deviation increase in such ties reduced violent crime from 8.3% in Buffalo to 23.6% in Cincinnati. The story is similar, though somewhat weaker in the property crime models in Table 5. An increase in the proportion of within block group ties among residents (specification 4) significantly reduces the property crime rate in three of the cities between 10 and 20%: the two exceptions are the two cities with the highest population density over block groups (Buffalo and Cleveland).

For the measure of cohesion not bounded at the block group unit and paralleling the earlier results for blocks, the *k*-core measure appears to be associated with lower crime rates. An increase in the value of the *k*-core measure—indicating a block group in which more members belong to robustly connected subgroups—is associated with lower violent crime rates in three of these cities (specification 6 in Table 4). However, it is associated with higher violent crime rates in Cincinnati. The performance for property crime rates is much better, as higher values are associated with significantly lower property crime rates in four of the cities (specification 6 in Table 5). A block group with a one standard deviation increase in the *k*-core value has 11.3% less property crime in Cleveland and 20.7% less property crime in Buffalo.

Our measure of information flow at the block group level—diffusion potential--again shows little evidence that it captures areas with lower crime rates (specification 7).

Aggregating network measures to tracts

Finally, when we move to the largest aggregation level—tracts—we see very weak results. There does appear to be evidence in specification 3 in Table 6 that a higher proportion of within-block ties for a tract leads to lower violent crime rates across all five cities. However, this effect is only significant for three of the cities in the property crime models in specification 3 in Table 7. The remaining measures in Tables 6 and 7 show weak or mixed results when measured at the tract level. The declining predictive power of micro-network features at higher levels of aggregation is reassuring, insofar as it is consistent with the hypothesis that the observed patterns are due to neighborhood-level network structure, rather than to economic or other sources of variation. Neighborhood network theories lead us to expect that variations on small geographical scales (e.g. blocks) will prove predictive of local variations in crime rates. As one moves to larger and larger units, these sources of variation wash out, and we are left with the conventional effects typically seen at large scales. Although it is possible that there other types of network features that become predictive at these larger scales, such features would have to be motivated by theories other than those currently considered within the criminological literature.

Including the network measures simultaneously

We next turn to the models that include several of our network measures simultaneously. In these models, along with our control variables, we included mean degree, the proportion of within area ties based on three geographic units (blocks, block groups, and tracts), and the diffusion measure. We point out that we were not able to include the measures of mean K-Cores and mean degree simultaneously in the model due to their very high degree of correlation (which ranged from .85 to .98 over various aggregation levels in various cities).

The results of these models demonstrate that most of our findings when including the network measures of cohesion separately hold up when including them simultaneously. The effect of block level mean degree is even more robust here, as it is significantly related to lower levels of violent crime in all five cities in Table 8. A one standard deviation increase in mean degree in the block associated with 22% lower violent crime rates on average across these cities, and with 26% lower property crime rates on average in Table 9.

<<<Tables 8 and 9 about here>>>

In these same models we also directly compared the effect of measuring the proportion of internal ties based on these three geographic definitions: blocks, block groups and tracts. We see evidence that it is not just within-block ties that matter, but also within-tract ties. Across all five of these cities, increasing the proportion of within-block and within-tract ties decreases the violent crime and property crime rates. Across these five cities, on average a one standard deviation increase in the proportion of ties within the same block is associated with a 27% lower violent crime rate and a 16% lower property crime rate. The size of the effects for within tract, or within block group ties, is similar. Thus, we see fairly strong evidence that the presence of a higher proportion of more localized ties has a stronger negative effect on the amount of violent crime, even when controlling for these other network and geographic measures, as well as the standard ecological measures that predict rates of crime. This complements the earlier findings regarding the importance of more local properties at more local levels of aggregation.

The effects of the diffusion measure on violent and property crime are similar to the models that did not simultaneously account for block cohesion. That is, the effects are quite mixed. For two of the cities—Cleveland and Sacramento—higher diffusion potential is associated with lower violent and property crime rates. On the other hand, there is no evidence for such an effect in the other three cities.

Turning to the models aggregating our measures to block groups, the effects are again weaker than in the block-aggregated models, as seen in Tables 10 and 11. As an aside, it is interesting to note that our control variables also show much weaker effects aggregated to these large units, consistent with the notion that they act through local-level mechanisms that average out over large spatial units. Nonetheless, we see that the importance of more localized ties does not vanish even at these larger scales. For the violent crime models, it appears that the presence of more within-block ties (the most micro unit) is most important for reducing violent crime rates for all of the cities except for the city with the lowest population density (Tucson). For Tucson, it is instead the presence of more within block group ties that reduces violent crime rates. Thus, for reducing violent crime, it is the presence of very localized ties within the blocks contained within block groups that matters most. On the other hand, we see more mixed results in the property crime models. Whereas the presence of more within block group ties is most important for reducing property crime rates in Buffalo and Tucson, in the other three cities it is the presence of within block ties that are most important. The effect of mean degree in the block group remains relatively robust in these models (though somewhat weakened from the models that did not control for these other cohesion measures). The diffusion potential measure again shows very mixed results.

<<<Tables 10 and 11 about here>>>

Finally, the models aggregating the data to tracts in Tables 12 and 13 show that the proportion of within-block ties is the most consistent predictor of both violent and property crime rates. For four of the five cities, an increase in the proportion of within-block ties in these tracts reduces the level of violent crime; the one exception is Sacramento, in which it is a higher proportion of within block group ties that matters. The effects are somewhat weaker for property crime, as within block ties are only important in two of the cities. The presence of within block group ties appears more important for the two cities with the lowest population density. The effects for mean degree in the tract are weaker: there is virtually no impact on violent crime rates, and it reduces property crime rates in three of the cities. Again, the diffusion potential measure shows mixed results.

It is interesting to note that the effects for within block ties are even more consistent than the effect of most of our control variables: the only really consistent predictor over all five of these cities in the violent crime models was the presence of vacant units (though even this measure was not significant in Tucson). In the property crime models, virtually none of the control variables showed a consistently significant effect over all five of these cities. We highlight these non-findings to emphasize that we are holding our simulated network measures to a particularly high standard in demanding that they show quite consistent replication over all five of these cities.

<<<Tables 12 and 13 about here>>>

Conclusion

This study began by positing that important insights can be obtained by combining information on the tendency of social ties to form based on spatial distribution with the actual geographic distribution of households in a community, and simulating the resultant social network of ties among residents. Even when specifying a very simple social interaction function in which residents form ties entirely based on propinquity, we showed that the social network measures of cohesion show a surprisingly strong negative relationship with the actual level of crime in the neighborhood. Of course, we do not know for certain whether such ties actually exist in these neighborhoods, and certainly the simulation would be wrong for some neighborhoods as it is a probabilistic model that captures general tendencies towards formation of social ties (although, as shown by Butts (2003; 2010), the baseline effects modeled here are extremely powerful predictors of structural properties under quite general conditions, and there is thus good reason to expect the models to be fairly robust). Despite those caveats, we observe that it would be difficult to explain away the predictive power of the network model without invoking some systematic bias that caused lower rates of crime to occur in the neighborhoods in which we also inaccurately simulated more cohesive networks. We know of no bias that would produce such results. Indeed, the robustness of the ability of putative network characteristics to predict crime above and beyond statistical controls -- and without requiring information on idiosyncratic cultural or other characteristics of neighborhoods -- would seem to stand as a strong vindication for structural theories of crime inhibition. Although founded on the simple insight that the geographic distribution of persons can affect the formation of social ties—which may then affect crime rates—these strong and systematic results suggest exciting new theoretical possibilities for criminologists by incorporating more sophisticated models of tie formation.

Considering the three categories of effects examined here, we found that our measures of local cohesion showed a clear and interpretable pattern of results. These findings go beyond past research that often only conceptualizes local cohesion in terms of mean degree. Scholars have generally not made this explicit, which has arguably only stunted the theoretical development of a network conceptualization of the importance of social ties for reducing neighborhood crime. Our results using these simulated ties showed that, although mean degree is consequential, within-area ties were equally important for explaining areas with lower rates of crime. This finding for the importance of within-area ties generally held across the varying sized geographic units (blocks, block groups, and tracts). This result suggests that the cohesion fostered by such ties may indeed be important to consider, and suggests that if studies were actually able to collect information on the full network of ties within a larger community, the presence of a higher proportion of these inward focused ties would be important for detecting higher levels of perceived cohesion. Future research will need to assess whether this is indeed the case.

There was some evidence that our measure of cohesion across geographic units (*k*-cores) was associated with lower crime rates. Thus, blocks containing more persons linked into larger cores in the city generally had lower violent and property crime rates (the one exception was Cincinnati). This is consistent with the notion that the provision of public control, as obtained from these more far flung networks, is important for reducing crime in the local neighborhood. This is consistent with the hypothesis of Bellair (1997) regarding the importance of such broader networks. This effect was present, although weaker, when measuring this broader linkage for residents in the larger units of block groups.

On the other hand, the network measure we constructed to capture information flow did a much poorer job of predicting crime location. One possibility is that there may be alternative network measures that would better facilitate the type of information flow that is important for crime fighting. Ours was simply an initial exploration into this approach, and leaves open the need for additional consideration of possible measures. For example, the research of Bellair (1997) suggested that the presence of ties into the broader community might be important for such information flow. Although our measure of the proportion of internally focused ties captured cohesion—and indeed showed a strong negative effect on crime rates, which would seem to contradict Bellair—it may be that certain measures capturing such external information may be useful. For instance, one approach might compute the average number of blocks each resident in a block is linked to. This would assume that multiple ties to an external block would be redundant, and therefore the presence of a single tie to an external block would provide the necessary information. A twist on this would be to use the block as the unit of analysis, and compute the total number of external blocks the block is tied to (defined as any tie between a resident on the block and a resident in an external block). Here, the possible flow of information from an external block would enter the awareness of the block, and then could be transmitted among the block members. This might even imply an interaction between the presence of such external ties to blocks, and the density of within-area ties (which would be useful for then transmitting this information to fellow block members).

Alternately, it may be the case that, in modern American communities, information access per se is not the main limiting factor on crime control. With many ways of becoming informed about their environments, it may be less diffiult for residents in urban neighborhoods to discover problems in their environment than to mobilize in taking action against those problems. If this is so, then we would indeed expect cohesion to be a better predictor of crime control than structures associated with open information flow. Even more provocative is the possibility that informationally "transparent" neighborhoods actually facilitate criminal activity, just as they facilitate its discovery. For instance, knowing when a neighbor will be out of town simultaneously makes it easier to know when to watch for signs of trouble, and to identify the best time to break into his or her house. Insofar as this is the case, information flow may have complex and inconsistent effects on crime rates (Pattillo 1998). Such questions require more in-depth analysis, and highlight the rich potential that this approach provides for further research by ecology of crime scholars.

An interesting finding of the present study was that most of the observed effects were strongest when aggregating these network measures to the very small geographic unit of blocks. Thus, these appear to be very micro-level processes (roughly on the order of a neighborhood or city block). When aggregating these measures to larger units, the relationships among variables frequently appeared considerably weaker. Of course, the fact that our control variables also appeared to perform much better when disaggregated to smaller units suggests that many of these ecological processes may operate at much smaller geographic units than is often posited in the criminology literature, suggesting the importance of carefully considering the appropriate unit of analysis (Hipp 2007a). In particular, we note that the theoretical rationale given for these effects -- processes such as the formation of collective efficacy -- is founded on phenomena that take place at small spatial scales. The coincidence of our effect strength pattern with the theorized effect scale further strengthens the argument that such micro-level mechanisms are indeed at work here.

It is worth pointing out that our results were also robust to two different point pattern placements and two different spatial interaction functions. That is, given that we only knew the number of housing units within blocks, and not their actual spatial location, we utilized two different approaches to placing these housing units in space. Likewise, although very little is known about the actual spatial interaction functions (SIF) of residents, we used two different SIF's from published research. The fact that our results were robust to these various specifications suggests that these may not be fragile findings, but may in fact be robust to various additional SIF's that we might specify. Nonetheless, future research will need to assess the degree to which this is indeed the case.

Although we have highlighted some interesting possibilities in this line of research simulating networks based on structural properties, we emphasize that this is only an initial step in an exciting new line of research. An obvious next step is to incorporate homophily effects. Many studies in the social network literature have shown the importance of similarity among persons based on various socio-demographic characteristics for creating social ties (McPherson, Smith-Lovin, and Cook 2001) . Most prominent would be to take into account the fact that social tie formation is inhibited by racial/ethnic difference, economic difference, and age differences (Kalmijn and Vermunt 2007). By incorporating these covariate effects into our simulated networks, we will be able to take into account social distance, as well as physical distance, when estimating the formation of networks (Butts and Carley 2000; Hipp and Perrin 2009). In the present study, we followed the common strategy of simply including a measure of racial/ethnic heterogeneity as a proxy for this. In future work, this information could be incorporated into the simulation of tie choice, and the network measures of cohesion and information flow would then be created from this simulated network. A challenge to this additional direction is that there is little empirical evidence regarding the actual size of these homophily parameters. Properly estimating such parameters requires information on both actual tie choice, as well as the total choice set (e.g., who lives nearby). Existing literature almost never provides such estimates.

Another limitation of this study was the focus on just five cities. We estimated the model separately on the five cities as five independent tests of our network measures in an effort to assess the robustness of our findings. Nonetheless, assessing these measures on additional cities would be necessary to understand how generalizable our findings are. Nonetheless, it is worth emphasizing that our network measures generally did just as well, and frequently much better, than the typical measures included in models predicting the ecological distribution of crime.

In conclusion, we believe our study has demonstrated an exciting new way for criminologists to think about how to integrate the possible importance of social networks into studies of the ecological distribution of crime in cities. Rather than simply asking whether *more social ties* exist in a neighborhood, we have suggested that it is useful to consider the actual structure of the network of a community. The challenges of such data collection have arguably stunted any theoretical development in this direction. Our novel approach of specifying social networks based on various propinquity preferences and the actual spatial distribution of households in the city, and then calculating various network structural measures based on the resultant social network suggests an exciting new direction for researchers. Future work incorporating other characteristics of tie formation and dissolution—including homophily preferences, as well as how mobility decisions affect the spatial distribution of ties—as well as other network structural measures that might capture important neighborhood characteristics, will allow further development of this approach.

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Tables and Figures

Table 1. Summary statistics for five cities, using the quasi Festinger point pattern

	Buffalo		Cincinnati		Cleveland		Sacramento		Tucson	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Blocks										
Density	0.122	0.218	0.219	0.515	0.178	0.390	0.126	0.202	0.138	0.230
Mean degree	7.238	3.358	5.940	3.241	7.337	3.250	5.748	2.606	4.649	2.195
Proportion ties within block	0.490	0.147	0.483	0.194	0.444	0.153	0.491	0.153	0.499	0.166
Proportion ties within block group	0.768	0.139	0.791	0.155	0.760	0.144	0.852	0.132	0.829	0.136
Proportion ties within tract	0.911	0.112	0.889	0.130	0.859	0.136	0.931	0.101	0.924	0.105
K-cores	4.284	1.680	3.549	1.664	4.377	1.629	3.434	1.329	2.845	1.139
Diffusion potential	21.235	7.572	10.661	4.709	44.790	6.565	23.865	9.242	39.550	9.418
Population density (in 1,000's)	4.699	4.535	5.282	55.868	4.326	5.061	3.801	21.327	2.669	4.448
Block groups										
Density	0.016	0.037	0.013	0.057	0.014	0.050	0.011	0.057	0.006	0.004
Mean degree	7.658	2.842	6.236	2.881	8.005	2.817	6.102	2.539	5.315	2.116
Proportion ties within block	0.539	0.102	0.596	0.131	0.508	0.110	0.579	0.130	0.594	0.116
Proportion ties within block group	0.764	0.096	0.797	0.101	0.755	0.100	0.852	0.084	0.825	0.080
Proportion ties within tract	0.912	0.071	0.892	0.085	0.864	0.094	0.939	0.053	0.924	0.059
K-cores	4.226	1.498	3.500	1.400	4.432	1.454	3.325	1.179	2.896	0.896
Diffusion potential	20.909	7.323	10.927	4.143	44.432	6.050	22.984	9.494	40.044	6.129
Population density (in 1,000's)	4.256	2.931	3.172	2.517	3.908	1.837	2.826	1.385	2.239	1.086
Tracts										
Density	0.005	0.018	0.006	0.013	0.006	0.009	0.004	0.012	0.001	0.001
Mean degree	7.698	2.487	6.301	2.920	7.810	2.872	6.270	2.449	5.478	1.922
Proportion ties within block	0.565	0.115	0.612	0.128	0.529	0.109	0.607	0.136	0.624	0.097
Proportion ties within block group	0.799	0.074	0.809	0.093	0.774	0.085	0.876	0.068	0.860	0.060
Proportion ties within tract	0.908	0.051	0.876	0.088	0.846	0.089	0.936	0.047	0.927	0.040
K-cores	4.015	1.343	3.452	1.413	4.172	1.514	3.241	1.150	2.864	0.728
Diffusion potential	20.198	7.614	10.741	4.126	43.234	7.304	22.453	9.898	39.271	7.032
Population density (in 1,000's)	3.899	1.868	3.083	2.824	3.568	1.895	2.626	1.256	2.016	0.801

Note: population density measured in 1,000's of persons per square mile

Table 2. Models with violent crime as the outcome, models over five cities in study. Units of analysis are blocks

	Buffalo		Cincinnati		Cleveland		Sacramento		Tucson	
(1) Tie density	3.0567	**	3.6789	**	1.5964	**	0.6186		2.0223	**
	(6.73)		(10.43)		(6.42)		(1.37)		(3.65)	
(2) Mean degree	-0.0662	**	0.0141		-0.0793	**	-0.1614	**	-0.2198	**
	-(7.61)		(1.35)		-(13.10)		-(16.36)		-(15.36)	
(3) Proportion of ties within block	-1.9026	**	-2.5792	**	-2.0386	**	-0.9125	**	-2.1656	**
	-(8.82)		-(15.34)		-(14.02)		-(4.82)		-(10.27)	
(4) Proportion of ties within block group	-1.3940	**	-2.0848	**	-1.6620	**	-1.8756	**	-4.0960	**
	-(6.73)		-(9.14)		-(11.59)		-(8.51)		-(16.41)	
(5) Proportion of ties within tract	-1.5660	**	-2.2417	**	-2.0376	**	-2.5962	**	-3.9127	**
	-(6.76)		-(8.29)		-(13.36)		-(9.07)		-(12.87)	
(6) K-cores	-0.108	**	0.0951	**	-0.1234	**	-0.3016	**	-0.352	**
	-(5.91)		(4.43)		-(9.69)		-(14.57)		-(11.44)	
(7) Diffusion potential	0.0152	**	0.0130	†	-0.0555	**	-0.0132	**	-0.0051	
	(3.27)		(1.66)		-(10.16)		-(4.56)		-(1.10)	

** *$p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*

Note: All models include all control variables described in text at this unit of analysis

Table 3. Models with property crime as the outcome, models over five cities in study. Units of analysis are blocks

	Buffalo	Cincinnati	Cleveland	Sacramento	Tucson
(1) Tie density	1.417 **	2.03 **	0.9507 **	-0.3306	1.7463 **
	(4.75)	(8.15)	(6.33)	-(1.04)	(4.78)
(2) Mean degree	-0.1072 **	-0.0337 **	-0.0737 **	-0.1394 **	-0.2250 **
	-(19.93)	-(4.72)	-(20.25)	-(19.82)	-(24.16)
(3) Proportion of ties within block	-0.5941 **	-1.7025 **	-1.0334 **	-0.3380 *	-1.8275 **
	-(4.55)	-(14.62)	-(12.27)	-(2.53)	-(13.26)
(4) Proportion of ties within block group	-0.9817 **	-1.5369 **	-0.9671 **	-1.5559 **	-3.4286 **
	-(7.32)	-(10.31)	-(11.38)	-(9.76)	-(21.05)
(5) Proportion of ties within tract	-1.2044 **	-1.7887 **	-1.3085 **	-1.5753 **	-3.7910 **
	-(7.49)	-(9.81)	-(14.13)	-(7.52)	-(18.24)
(6) K-cores	-0.1918 **	-0.0117	-0.1208 **	-0.2554 **	-0.353 **
	-(17.22)	-(0.80)	-(15.77)	-(17.59)	-(17.61)
(7) Diffusion potential	-0.0051 †	0.0116 *	-0.0514 **	-0.0185 **	-0.0071 *
	-(1.83)	(2.37)	-(15.38)	-(9.06)	-(2.21)

*** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*

Note: All models include all control variables described in text at this unit of analysis

Table 4. Models with violent crime as the outcome, models over five cities in study. Units of analysis are block groups

	Buffalo	Cincinnati	Cleveland	Sacramento	Tucson
(1) Tie density	20.7431 **	-13.26 *	1.0793	-1.8942	88.6798 **
	(3.19)	-(2.42)	(0.17)	-(0.34)	(8.01)
(2) Mean degree	-0.0358 *	0.0330 †	-0.0203 *	-0.0657 **	-0.0914 **
	-(2.57)	(1.70)	-(2.00)	-(2.82)	-(3.52)
(3) Proportion of ties within block	-0.8518 *	-2.0524 **	-1.2747 **	-0.8384 *	-1.0363 **
	-(2.04)	-(6.00)	-(4.91)	-(2.25)	-(2.59)
(4) Proportion of ties within block group	-1.4528 **	-1.5893 **	-0.7527 **	-1.6880 **	-3.5093 **
	-(3.47)	-(3.40)	-(2.59)	-(2.82)	-(5.91)
(5) Proportion of ties within tract	-0.3318	-0.1785	-1.1529 **	-2.5479 **	-2.5424 **
	-(0.64)	-(0.29)	-(3.55)	-(2.69)	-(3.16)
(6) K-cores	-0.0686 **	0.0805 *	-0.0153	-0.1123 *	-0.207 **
	-(2.71)	(2.16)	-(0.79)	-(2.25)	-(3.82)
(7) Diffusion potential	0.0154 *	-0.0008	-0.0221 **	0.0024	-0.0121
	(2.53)	-(0.06)	-(2.78)	(0.49)	-(1.39)

*** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*

Note: All models include all control variables described in text at this unit of analysis

Table 5. Models with property crime as the outcome, models over five cities in study. Units of analysis are block groups

	Buffalo		Cincinnati		Cleveland		Sacramento		Tucson	
(1) Tie density	16.8557	**	-27.368	**	4.6143		-11.4377	*	49.7576	**
	(3.36)		-(6.40)		(1.05)		-(2.13)		(4.75)	
(2) Mean degree	-0.0831	**	-0.0071		-0.0491	**	-0.0706	**	-0.0590	*
	-(8.34)		-(0.44)		-(7.11)		-(3.31)		-(2.49)	
(3) Proportion of ties within block	0.9712	**	-1.4532	**	0.2517		-0.4004		-0.5960	†
	(3.19)		-(5.03)		(1.43)		-(1.17)		-(1.69)	
(4) Proportion of ties within block group	-0.4454		-1.0761	**	-0.2745		-1.2362	*	-2.6543	**
	-(1.42)		-(2.79)		-(1.33)		-(2.22)		-(4.86)	
(5) Proportion of ties within tract	-0.4950		0.2798		-0.5540	*	-1.1866		-1.8964	**
	-(1.21)		(0.54)		-(2.33)		-(1.41)		-(2.65)	
(6) K-cores	-0.1547	**	-0.0025		-0.0823	**	-0.1287	**	-0.1663	**
	-(8.60)		-(0.08)		-(6.17)		-(2.91)		-(3.41)	
(7) Diffusion potential	0.0021		0.0050		-0.0477	**	-0.0062		-0.0116	
	(0.47)		(0.54)		-(10.30)		-(1.38)		-(1.52)	

** *$p < .01$ (two-tail test)*, * *$p < .05$ (two-tail test)*, † *$p < .05$ (one-tail test). T-values in parentheses.*

Note: All models include all control variables described in text at this unit of analysis

Table 6. Models with violent crime as the outcome, models over five cities in study. Units of analysis are tracts

	Buffalo		Cincinnati		Cleveland		Sacramento		Tucson	
(1) Tie density	-21.2313		-62.957	**	27.9033	*	-18.838	**	46.315	
	-(0.87)		-(6.10)		(2.53)		-(2.88)		(0.84)	
(2) Mean degree	0.0159		0.0207		-0.0221	†	0.0637		-0.0399	
	(0.62)		(0.60)		-(1.72)		(1.48)		-(1.12)	
(3) Proportion of ties within block	-1.9824	**	-2.5170	**	-1.5352	**	-2.6518	**	-2.4969	**
	-(3.00)		-(4.46)		-(4.73)		-(5.30)		-(4.62)	
(4) Proportion of ties within block group	-1.2295	†	-0.0433		-0.9687	*	-5.1551	**	-4.6877	**
	-(1.71)		-(0.05)		-(2.29)		-(4.75)		-(4.79)	
(5) Proportion of ties within tract	0.7431		2.3428	*	-1.8256	**	-4.5445	**	-3.3488	*
	(0.73)		(2.33)		-(4.33)		-(2.94)		-(2.34)	
(6) K-cores	0.0617		0.0695		-0.0168		0.1745	*	-0.017	
	(1.31)		(1.10)		-(0.69)		(2.20)		-(0.20)	
(7) Diffusion potential	0.0290	**	-0.0009		-0.0051		0.0135	†	0.0213	**
	(3.44)		-(0.05)		-(0.51)		(1.89)		(2.64)	

*** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*

Note: All models include all control variables described in text at this unit of analysis

Table 7. Models with property crime as the outcome, models over five cities in study. Units of analysis are tracts

	Buffalo	Cincinnati	Cleveland	Sacramento	Tucson
(1) Tie density	23.1315	-77.827 **	32.0455 **	-26.421 **	-21.58
	(1.21)	-(10.80)	(4.14)	-(3.19)	-(0.46)
(2) Mean degree	-0.0197	-0.0239	-0.0453 **	-0.0337	-0.0159
	-(0.95)	-(0.73)	-(5.12)	-(0.73)	-(0.46)
(3) Proportion of ties within block	-0.3595	-1.7983 **	-0.3977	-1.2653 *	-1.5665 **
	-(0.64)	-(3.14)	-(1.61)	-(2.25)	-(3.09)
(4) Proportion of ties within block group	0.0210	0.8071	-0.5220 †	-4.2391 **	-3.2456 **
	(0.04)	(0.90)	-(1.72)	-(3.49)	-(3.46)
(5) Proportion of ties within tract	-0.0916	2.6961 **	-1.1422 **	-1.7377	-1.9295
	-(0.11)	(2.74)	-(3.71)	-(1.09)	-(1.44)
(6) K-cores	-0.0406	-0.0158	-0.0726 **	0.0026	0.0449
	-(1.09)	-(0.26)	-(4.25)	(0.03)	(0.56)
(7) Diffusion potential	0.0124 †	0.0069	-0.0314 **	0.0013	0.0202 **
	(1.87)	(0.38)	-(4.42)	(0.16)	(2.95)

** *$p < .01$ (two-tail test)*, * *$p < .05$ (two-tail test)*, † *$p < .05$ (one-tail test). T-values in parentheses.*

Note: All models include all control variables described in text at this unit of analysis

Table 8. Models with violent crime as the outcome, models over five cities in study. Including network measures simultaneously in the model. Units of analysis are blocks

	Buffalo		Cincinnati		Cleveland		Sacramento		Tucson	
Mean degree	-0.0897	**	-0.0422	**	-0.0792	**	-0.1593	**	-0.1938	**
	-(10.37)		-(4.17)		-(12.51)		-(15.97)		-(14.16)	
Proportion of ties within block	-2.0812	**	-2.6728	**	-2.2997	**	-1.3208	**	-1.0643	**
	-(8.30)		-(12.93)		-(13.95)		-(6.33)		-(4.47)	
Proportion of ties within block group	-0.2582		-0.0836		-0.3000		-0.6855	*	-2.6954	**
	-(1.04)		-(0.27)		-(1.60)		-(2.51)		-(8.32)	
Proportion of ties within tract	-0.8614	**	-1.1418	**	-0.9686	**	-1.2586	**	-1.2892	**
	-(3.49)		-(3.44)		-(5.38)		-(3.74)		-(3.65)	
Diffusion potential	0.0154	**	-0.0123		-0.0410	**	-0.0095	**	-0.0056	
	(3.41)		-(1.63)		-(7.69)		-(3.34)		-(1.23)	
Percent black	0.0057	**	0.0035	**	0.0073	**	0.0186	**	0.0184	**
	(6.68)		(4.03)		(11.87)		(9.70)		(3.63)	
Percent Latino	0.0025		0.0162	*	0.0036	*	0.0158	**	0.0176	**
	(1.23)		(2.03)		(2.29)		(9.55)		(16.76)	
Racial/ethnic heterogeneity	0.8114	**	0.5032	**	0.6331	**	0.4756	**	0.7614	**
	(5.74)		(3.34)		(5.93)		(2.68)		(4.10)	
Percent single parent households	0.0057	**	0.0133	**	0.0049	**	0.0050	*	0.0069	**
	(3.15)		(7.39)		(3.89)		(2.20)		(2.62)	
Percent occupied units	-0.0231	**	-0.0218	**	-0.0141	**	-0.0249	**	-0.0104	**
	-(10.21)		-(8.27)		-(7.82)		-(6.62)		-(2.67)	
Percent owners	-0.0108	**	-0.0129	**	-0.0147	**	-0.0188	**	-0.0111	**
	-(8.32)		-(10.85)		-(18.01)		-(18.88)		-(10.49)	
Intercept	0.2923		0.9918	**	2.3562	**	2.4912	**	1.5668	**
	(0.94)		(2.84)		(7.69)		(5.68)		(3.13)	

*** $p < .01$(two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*

Table 9. Models with property crime as the outcome, models over five cities in study. Including network measures simultaneously in the model. Units of analysis are blocks

	Buffalo		Cincinnati		Cleveland		Sacramento		Tucson	
Mean degree	-0.1216	**	-0.0866	**	-0.0717	**	-0.1367	**	-0.2100	**
	-(22.21)		-(12.13)		-(18.92)		-(18.63)		-(23.86)	
Proportion of ties within block	-1.0985	**	-2.041	**	-1.6449	**	-0.9704	**	-1.1563	**
	-(7.16)		-(14.18)		-(17.20)		-(6.48)		-(7.64)	
Proportion of ties within block group	-0.5521	**	-0.2615		-0.2148	*	-1.0148	**	-1.8715	**
	-(3.49)		-(1.27)		-(1.98)		-(5.27)		-(9.24)	
Proportion of ties within tract	-0.5445	**	-0.8943	**	-0.5830	**	-0.4757	*	-1.8189	**
	-(3.30)		-(3.91)		-(5.46)		-(1.97)		-(7.68)	
Diffusion potential	0.0002		-0.0019		-0.0405	**	-0.0135	**	-0.0042	
	(0.07)		-(0.39)		-(13.36)		-(6.61)		-(1.54)	
Percent black	-0.0002		-0.0028	**	0.0020	**	0.0070	**	0.0066	*
	-(0.40)		-(4.68)		(5.87)		(4.87)		(1.99)	
Percent Latino	-0.0029	*	-0.0023		-0.0015		0.0072	**	0.0074	**
	-(2.01)		-(0.39)		-(1.62)		(5.84)		(11.05)	
Racial/ethnic heterogeneity	0.8891	**	0.3246	**	0.4999	**	-0.0954		0.7330	**
	(9.41)		(3.14)		(8.02)		-(0.78)		(6.26)	
Percent single parent households	-0.0010		0.0054	**	0.0004		0.0038	*	0.0051	**
	-(0.86)		(4.32)		(0.56)		(2.25)		(2.84)	
Percent occupied units	-0.0105	**	-0.0140	**	-0.0093	**	-0.0177	**	-0.0066	*
	-(7.09)		-(7.26)		-(8.56)		-(6.53)		-(2.44)	
Percent owners	-0.0129	**	-0.0107	**	-0.0100	**	-0.0119	**	-0.0092	**
	-(15.98)		-(13.47)		-(21.51)		-(16.24)		-(13.44)	
Intercept	1.7174	**	2.3870	**	3.0292	**	2.5893	**	4.0044	**
	(8.51)		(9.45)		(16.98)		(7.97)		(11.83)	

*** $p < .01$(two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*

Table 10. Models with violent crime as the outcome, models over five cities in study. Including network measures simultaneously in the model. Units of analysis are block groups

	Buffalo	Cincinnati	Cleveland	Sacramento	Tucson
Mean degree	-0.0761 **	-0.0549 *	-0.0296 *	-0.0949 **	-0.0696 *
	-(4.59)	-(2.38)	-(2.57)	-(4.22)	-(2.50)
Proportion of ties within block	-1.3831 *	-2.6027 **	-2.3594 **	-1.0702 *	0.1843
	-(2.37)	-(5.09)	-(6.79)	-(2.14)	(0.33)
Proportion of ties within block group	-1.1655 *	-0.8402	0.4916	-0.7185	-4.0748 **
	-(2.23)	-(1.12)	(1.24)	-(0.88)	-(4.79)
Proportion of ties within tract	0.3345	1.4062 †	-0.6449 †	-1.5180	0.2576
	(0.62)	(1.81)	-(1.71)	-(1.41)	(0.27)
Diffusion potential	0.0154 *	-0.0033	-0.0402 **	-0.0028	-0.0142
	(2.54)	-(0.28)	-(4.27)	-(0.53)	-(1.38)
Percent black	0.0065 **	0.0014	0.0059 **	0.0068	0.0218 *
	(5.61)	(0.95)	(5.91)	(1.23)	(2.01)
Percent Latino	0.0008	0.0191	0.0023	0.0110 *	0.0121 **
	(0.24)	(1.13)	(0.80)	(2.52)	(5.65)
Racial/ethnic heterogeneity	0.0096 **	0.0066 **	0.0071 **	-0.0059	0.0052
	(4.61)	(2.87)	(4.13)	-(1.42)	(1.38)
Concentrated disadvantage	0.1508 **	0.4426 **	0.1886 **	0.4369 **	0.1432
	(3.93)	(7.41)	(5.83)	(6.29)	(1.63)
Inequality (Gini)	0.0085 †	-0.0134 *	0.0084 *	-0.0043	0.0035
	(1.69)	-(2.15)	(2.16)	-(0.59)	(0.56)
Percent occupied units	-0.0186 **	-0.0172 **	-0.0182 **	-0.0302 **	0.0057
	-(5.14)	-(2.96)	-(5.55)	-(3.56)	(0.71)
Percent owners	-0.0040 †	-0.0101 **	-0.0070 **	-0.0091 **	-0.0070 **
	-(1.69)	-(3.57)	-(3.90)	-(3.27)	-(2.84)
Intercept	-1.7220 **	-0.7093	0.6520	3.0196 **	-1.0636
	-(2.63)	-(0.83)	(1.16)	(2.62)	-(0.85)

*** $p < .01$(two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*

Table 11. Models with property crime as the outcome, models over five cities in study. Including network measures simultaneously in the model. Units of analysis are block groups

	Buffalo	Cincinnati	Cleveland	Sacramento	Tucson
Mean degree	-0.0956 **	-0.0921 **	-0.0305 **	-0.0949 **	-0.041
	-(7.64)	-(5.03)	-(4.12)	-(4.39)	-(1.57)
Proportion of ties within block	0.0098	-2.4497 **	-1.3572 **	-0.9551 *	0.3106
	(0.02)	-(5.95)	-(5.83)	-(2.04)	(0.61)
Proportion of ties within block group	-1.0651 **	-0.8268	-0.3037	-1.2959 †	-3.2024 **
	-(2.74)	-(1.40)	-(1.15)	-(1.67)	-(4.07)
Proportion of ties within tract	-0.0111	1.9449 **	-0.1248	-0.4018	0.1135
	-(0.03)	(3.03)	-(0.49)	-(0.42)	(0.13)
Diffusion potential	0.0092 *	0.0111	-0.0590 **	-0.0106 *	-0.0117
	(2.21)	(1.19)	-(10.94)	-(2.12)	-(1.24)
Percent black	-0.0010	-0.0036 **	0.0023 **	0.0006	0.0022
	-(1.10)	-(2.92)	(3.55)	(0.11)	(0.21)
Percent Latino	-0.0045 †	0.0166	-0.0014	0.0043	0.0032 †
	-(1.75)	(1.06)	-(0.76)	(1.01)	(1.67)
Racial/ethnic heterogeneity	0.0091 **	0.0049 **	0.0058 **	-0.0117 **	0.0038
	(5.79)	(2.66)	(5.19)	-(3.03)	(1.14)
Concentrated disadvantage	-0.0237	0.2324 **	0.0193	0.2709 **	-0.0323
	-(0.81)	(4.82)	(0.90)	(4.15)	-(0.40)
Inequality (Gini)	0.0081 *	-0.0065	0.0038	-0.0108	0.0109 †
	(2.06)	-(1.31)	(1.51)	-(1.58)	(1.90)
Percent occupied units	-0.0102 **	-0.0120 **	-0.0097 **	-0.0312 **	0.0018
	-(3.77)	-(2.59)	-(4.52)	-(4.01)	(0.25)
Percent owners	-0.0097 **	-0.0137 **	-0.0078 **	-0.0098 **	-0.0050 *
	-(5.45)	-(5.93)	-(6.69)	-(3.90)	-(2.25)
Intercept	0.1874	0.5410	2.7719 **	4.7789 **	1.0519
	(0.37)	(0.77)	(7.85)	(4.44)	(0.92)

*** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*

Table 12. Models with violent crime as the outcome, models over five cities in study. Including network measures simultaneously in the model. Units of analysis are tracts

	Buffalo	Cincinnati	Cleveland	Sacramento	Tucson
Mean degree	-0.0096	-0.0581 †	-0.0214	-0.0116	-0.03
	-(0.38)	-(1.71)	-(1.49)	-(0.30)	-(0.95)
Proportion of ties within block	-2.2625 *	-4.9692 **	-2.5003 **	-2.3845 **	-0.96
	-(2.12)	-(6.43)	-(5.51)	-(3.04)	-(1.18)
Proportion of ties within block group	0.6470	2.3505	1.7752 **	-2.1444	-3.4284 *
	(0.54)	(1.53)	(2.70)	-(1.29)	-(2.10)
Proportion of ties within tract	1.1357	3.4018 **	-1.6268 **	-1.3352	1.2106
	(1.05)	(2.73)	-(2.88)	-(0.80)	(0.71)
Diffusion potential	0.0226 **	0.0221	-0.0218 †	-0.0136	0.0098
	(2.64)	(1.23)	-(1.83)	-(1.63)	(1.10)
Percent black	0.0063 **	0.0025	0.0064 **	-0.0068	0.0709 **
	(3.22)	(0.98)	(5.19)	-(0.67)	(2.83)
Percent Latino	-0.0019	-0.0630	0.0017	-0.0015	0.0093 **
	-(0.32)	-(1.37)	(0.44)	-(0.18)	(3.06)
Racial/ethnic heterogeneity	0.0028	0.0114 **	0.0093 **	0.0081	0.0022
	(0.80)	(3.30)	(4.26)	(1.02)	(0.39)
Concentrated disadvantage	0.1044	0.3348 **	0.2139 **	0.4888 **	0.3563 *
	(1.24)	(3.58)	(5.77)	(4.12)	(2.15)
Inequality (Gini)	-0.0102	-0.0150	0.0047	0.0208	0.0410 **
	-(0.88)	-(1.46)	(0.85)	(1.35)	(3.63)
Percent occupied units	-0.0383 **	-0.0199 *	-0.0180 **	-0.0691 **	0.0062
	-(4.29)	-(1.98)	-(4.21)	-(3.95)	(0.45)
Percent owners	-0.0120 †	-0.0155 **	-0.0032	0.0024	-0.0009
	-(1.95)	-(3.08)	-(1.20)	(0.45)	-(0.24)
Intercept	-1.1804	-4.2639 **	0.1528	6.9245 **	-1.2652
	-(1.05)	-(3.16)	(0.23)	(3.26)	-(0.64)

*** $p < .01$(two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*

Table 13. Models with property crime as the outcome, models over five cities in study. Including network measures simultaneously in the model. Units of analysis are tracts

	Buffalo	Cincinnati	Cleveland	Sacramento	Tucson
Mean degree	-0.0179	-0.08 *	-0.0336 **	-0.1026 *	-0.028
	-(0.80)	-(2.41)	-(3.27)	-(2.24)	-(0.88)
Proportion of ties within block	-0.9481	-4.7744 **	-1.3053 **	-1.4483 †	-0.232
	-(1.01)	-(6.32)	-(3.97)	-(1.69)	-(0.31)
Proportion of ties within block group	0.9786	3.4921 *	0.2717	-4.9894 **	-2.8686 †
	(0.93)	(2.23)	(0.57)	-(2.75)	-(1.84)
Proportion of ties within tract	-0.2619	3.4354 **	-0.5913	1.8427	1.4302
	-(0.29)	(2.85)	-(1.43)	(0.98)	(0.86)
Diffusion potential	0.0119 †	0.0405 *	-0.0344 **	-0.0156	0.0141 †
	(1.70)	(2.28)	-(4.10)	-(1.62)	(1.79)
Percent black	-0.0014	-0.0033	0.0032 **	-0.0025	0.0249
	-(0.82)	-(1.26)	(3.65)	-(0.22)	(1.04)
Percent Latino	-0.0104 †	-0.0224	-0.0016	-0.0024	0.0034
	-(1.91)	-(0.45)	-(0.57)	-(0.26)	(1.19)
Racial/ethnic heterogeneity	0.0042	0.0098 **	0.0081 **	-0.0022	0.0033
	(1.39)	(2.93)	(5.17)	-(0.25)	(0.62)
Concentrated disadvantage	-0.0228	0.1232	0.0189	0.3357 **	0.1188
	-(0.31)	(1.35)	(0.71)	(2.64)	(0.76)
Inequality (Gini)	-0.0049	0.0003	-0.0002	-0.0192	0.0377 **
	-(0.50)	(0.03)	-(0.05)	-(1.10)	(3.55)
Percent occupied units	-0.0173 *	-0.0132	-0.0113 **	-0.0374 †	0.0072
	-(2.25)	-(1.28)	-(3.73)	-(1.87)	(0.56)
Percent owners	-0.0164 **	-0.0221 **	-0.0066 **	-0.0068	-0.0022
	-(3.05)	-(4.55)	-(3.49)	-(1.15)	-(0.58)
Intercept	0.0814	-3.2199 *	2.0600 **	5.6554 *	-0.8432
	(0.08)	-(2.38)	(4.33)	(2.36)	-(0.45)

*** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses.*