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The spatial and temporal dynamics of neighborhood informal social control and crime

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ABSTRACT

Social disorganization theory is one of the most widely tested theories in criminology, yet few studies consider the temporal and spatial dynamics of neighborhood composition, neighborhood informal social control and crime. To better understand these relationships, we use census data, police data and three survey waves of data from a unique longitudinal dataset with over 4,000 respondents living across 148 neighborhoods in an Australian city undergoing rapid population growth. We employ cross-lagged reciprocal feedback models to test the central tenets of social disorganization theory and its contemporary advances for three crime types: violent crime, property crime and drug crime. Further, we examine the reciprocal relationship between neighborhood composition, three components of informal social control (neighborhood social ties, expectations for informal social control and the exercise of informal social control) and crime and whether socio-demographic changes in nearby neighborhoods shape these relationships over time. We find that changes in the socio-demographic composition in both focal and nearby areas influence neighborhood informal social control, however, in contrast to cross-sectional studies of social disorganization theory, our results reveal little support that neighborhood informal social control significantly decreases crime over time.

Key words: Social Disorganization, Collective Efficacy, Crime, Neighborhood

INTRODUCTION

Traditional and contemporary social disorganization theories posit that crime concentrates in communities where there is a limited capacity to regulate unwanted behavior. Three central arguments emerge from this scholarship. The first is that neighborhood poverty, racial/ethnic concentration and residential instability hinder informal social control, specifically, the development of neighborhood social ties and shared expectations for responding to neighborhood problems. Second, in the absence of ties and shared expectations, residents are unlikely to take necessary actions to regulate unwanted behavior. Third, the inability or unwillingness to *exercise* informal social control leads to higher crime rates (Bursik and Grasmick, 1993; Hunter, 1985; Kornhauser, 1978; Sampson and Groves, 1989; Sampson, Raudenbush and Earls, 1997; Shaw and McKay, 1942; Skogan, 1990).

Social disorganization theory is one of the most studied theories in criminology, and its popularity has increased substantially in the last twenty years. Yet there are certain limitations in the literature that we address herewith. Although the theory focusses on social processes that unfold over time and across place, due to excessive costs associated with the longitudinal study of neighborhood effects, survey research is almost exclusively cross-sectional. From these studies it is difficult to comprehensively test the central propositions of the theory, particularly that informal social control reduces crime over time, or assess whether or not there may be possible feedback effects between crime and informal social control. To this end, longitudinal social disorganization studies rely predominantly on administrative data, which do not capture the regulatory processes central to the theory. Only one data source in the Netherlands has the capacity to employ multiple waves of survey data to examine the longitudinal relationship between neighborhood composition, informal social control and crime (Hipp and Steenbeek, 2016; Steenbeek and Hipp, 2011). Results from this research suggest the association between neighborhood social ties, shared expectations for action and the exercise of informal social control and crime, as proposed by social disorganization theory, is not fully supported. Thus despite the significant body of social disorganization research, it remains unclear whether or not changes in neighborhood socio-demographic composition impact informal social control processes; if these changes have consequences for crime; whether and how crime influences the neighborhood composition and informal social control at a later time point; and if compositional changes in nearby areas also affect these relationships.

Scholarship is also surprisingly quiet on whether or not the components of informal social control are equally important for reducing/preventing different types of crime. There is nothing in traditional or contemporary advances of social disorganization theory to suggest that informal control operates differently for different types of crime. Yet, studies reveal that different crimes have different etiologies and the informal social control – crime association may differ for particular crime types (Hipp and Steenbeek, 2016).

Drawing on unique longitudinal survey data from over 4,000 residents living across 148 neighborhoods in Brisbane, Australia combined with census and police data, we provide a comprehensive test of social disorganization theory and its contemporary advances, focusing on the systemic model of community regulation and collective efficacy theory. Building on recent longitudinal research on neighborhoods in the Netherlands (Steenbeek and Hipp 2011; Hipp and Steenbeek 2016), we employ cross-lagged simultaneous equation modelling to answer three key questions. Our first question asks if changes in the neighborhood composition influence neighborhood social ties, shared expectations for informal social control and the exercise of informal social control over time. Our second question asks if informal social control influences violence, property and drug related crimes at a subsequent time point and if there are feedback effects of crime on informal social control. Our final question advances recent studies that find nearby areas are influential in explaining crime rates (Sampson, 2012), by asking whether and how the changing social-demographic context of surrounding neighborhoods influences both informal social control and crime in our focal neighborhoods.

In what follows, we focus our literature review on key components of community regulation outlined in social disorganization theory, the systemic model of community regulation and collective efficacy theory to highlight what we know about the relationship between informal social control and crime. We concentrate on *neighborhood social ties, shared expectations of informal social control* and the *exercise of informal social control* and their link to crime, as well as the possible feedback effects of crime on informal social control. Finally, we review studies that examine adjacency effects of nearby areas and consider how they might influence the informal social control-crime link in focal neighborhoods.

WHAT CONSTITUTES INFORMAL SOCIAL CONTROL?

For decades scholars have sought to identify the mechanisms that lead to higher crime in urban neighborhoods. Clifford Shaw and Henry McKay (1942) were the first to theorize why particular types of 'places' were more criminogenic than others. Moving away from individual level theories of criminality, they posited that disadvantage, residential mobility and ethnic heterogeneity made it difficult for local residents to realize common values and work together to prevent crime. In other words, the neighborhood composition promoted 'social disorganization', defined as the breakdown of informal social control, which in turn led to crime.

Early studies of social disorganization theory, and later the systemic model of community regulation, focused on the direct relationship between intra-neighborhood social ties and crime. For example, Sampson and Groves (1989) found communities with strong neighborhood ties and high levels of organizational participation had fewer muggings, robberies and burglaries. Bursik's (1999) study also revealed that strong neighborhood ties encouraged conformity and adherence to the law. Yet others found neighborhood social ties were not associated with lower crime (Warner and Rountree, 1997) and in some cases encouraged crime (Pattillo, 1998). These latter studies challenged the urban village approach underpinning earlier social disorganization research and pointed to the role that diffuse and transitory urban relationships might play in the maintenance of social order (Sampson, 2002).

Although social disorganization theory and the systemic model of community regulation contend that neighborhood social ties are important for crime control, a closer reading of this literature suggests the link between ties and crime is indirect, working through the development of *shared expectations of informal social control* and influencing *the exercise of informal social control behaviors* (Bursik and Grasmick, 1993; Sampson, Raudenbush and Earls, 1997). The evidence that this is the case is mixed. In the U.S., Warner (2014) finds that residents view requests for behavior change positively when they live in socially connected neighborhoods. Similarly a cross-sectional study of Australian neighborhoods reveals that social ties are positively associated with expectations of informal social control (Wickes et al., 2013) and the exercise of informal social control (Wickes et al 2017). Conversely, other research indicates the presence of strong social ties lead to lower expectations of informal social control (Browning, Dietz and Feinberg, 2004). While these studies do not explicitly model associations between neighborhood social ties, expectations for informal social control and the exercise of informal social control actions, they do suggest that the relationship between these mechanisms of informal social control may differ from that proposed in social disorganization theory.

The collective efficacy scholarship, representing the most recent advance of social disorganization theory, emphasizes the importance of agency and what ordinary residents do when faced with neighborhood problems. Collective efficacy, defined as "shared beliefs in a neighborhood's conjoint capability for action to achieve an intended effect" (Sampson, 2001: 95), is considered the key explanatory mechanism linking the composition of the neighborhood with crime (Sampson, Raudenbush and Earls, 1997). Collective efficacy theory de-emphasizes the role of ties and privileges the perceived willingness of local citizens to regulate unwanted behavior. Collective efficacy, therefore, represents a neighborhood's *expectations* for action and is best understood as the potential for informal social control action (Wickes, Hipp, Sargeant and Mazerolle, 2017).

Extensive literature[1] (largely cross-sectional) reveals a strong association between neighborhood expectations for informal social control and lower crime (e.g. Mazerolle, Wickes and McBroom, 2010; Sampson, Raudenbush and Earls, 1997; Sampson and Wikström, 2008; Zhang, Messner and Liu, 2007), however, only two studies examine whether shared expectations for informal social control lead to the *exercise of informal social control* or what residents actually do when they are faced with a neighborhood problem. Steenbeek and Hipp (2011) find that shared feelings of responsibility for neighborhood safety (measured using only a single item) had no relationship with whether or not residents had attempted to improve the livability and safety of the neighborhood (again measured with only a single item) at a later time point (Steenbeek and Hipp, 2011). Similarly a cross-sectional study in Australia finds no association between neighborhood collective efficacy and the exercise of either parochial or public informal social control (Wickes et al., 2017). Using multiple waves of survey, census and crime data and employing cross-lagged simultaneous equation models, Hipp and Wickes (2017) found that neighborhood perceptions of collective efficacy did not reduce violence over time.[2] Thus, although traditional and contemporary

[1] At the time of writing Sampson, Raudenbush and Earl's (1997) influential collective efficacy study published in *Science* has over 9,000 citations.
[2] A limitation of Hipp and Wickes' (2017) study is they did not distinguish between expectations for informal social control and informal social control actions. Thus is it is possible that what residents actually do in

interpretations of social disorganization theory propose that shared expectations for informal social control lead to informal social control actions and, further, that informal social control actions significantly decrease crime over time, there is insufficient longitudinal research to support these theoretical tenets.[3]

THE FEEDBACK EFFECTS OF CRIME

A further limitation of cross-sectional social disorganization research is that it fails to explicitly account for possible feedback effects, which are central to social disorganization theory but can also bias estimates in linear regression models. Though rarely tested, there is scattered evidence of important feedback effects from crime on informal social control, suggesting that crime, rather than other neighborhood changes, is more likely to damage informal social control. With the growing availability of longitudinal census and administrative data, studies show that crime has a deleterious effect on the neighborhood socio-demographic variables that are theoretically linked to informal social control. For example, crime increases residential mobility (Boggess and Hipp, 2010; Dugan, 1999; Hipp, Tita and Greenbaum, 2009; Xie and McDowall, 2008) and neighborhoods with high rates of violent or property crime experience population loss (Morenoff and Sampson, 1997) and higher vacancy rates (Hipp, 2010a; Taylor, 1995). In Australia, studies also reveal that increases in violent crime lead to increases in concentrated disadvantage at a later time point (Hipp and Wickes, 2017). Crime can also change the socio-economic composition through disproportionate residential mobility (Hipp, 2010b). Whereas high levels of crime are arguably undesirable for all residents, not all residents have equal ability to leave the

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response to local problems may be more influential for crime than what they think their neighbors will do. We test this explicitly in the current paper.

[3] A study in Chicago tested whether the level of collective efficacy reported in 1995 affected the level of change in homicides from 1991-93 to 1996-8 (Morenoff et al 2001). Although useful, the timing of the measurements could not rule out the possibility that homicides in 1991-93 impacted the level of collective efficacy reported in 1995.

neighborhood. If those with the most economic resources are the ones who exit, the neighborhood economy weakens (Hipp, 2010a).

This same disproportionate mobility process can also lead to a change in the racial composition of neighborhoods. In Chicago neighborhoods, higher delinquency rates in 1960 were associated with more non-whites in 1970 (Bursik, 1986). In neighborhoods across 13 U.S. cities, crime at one point was associated with a higher proportion African Americans ten years later (Hipp, 2010a). Studies focusing on household units have found that disproportionate housing turnover from white to non-white residents occurs after crime events (Xie and McDowall, 2010), occurs in micro-neighborhoods with more perceived crime (Hipp, 2010b), and in larger neighborhoods with higher violent crime rates (Hipp, 2011). Taken together, crime can be the catalyst for neighborhood socio-demographic change and these changes can, in turn, damage mechanisms of informal social control.

There is some evidence that this is indeed the case. Residents in high crime neighborhoods perceive less cohesion and less collective efficacy (Skogan, 1990; Steenbeek and Hipp, 2011). Moreover, higher levels of robbery lead to lower levels of cohesion (Markowitz et al., 2001) and reduced surveillance by residents (Bellair, 2000). Yet in the absence of longitudinal neighborhood studies, few explore these reciprocal relationships. Consequently, we know remarkably little about the feedback of effects of crime on both neighborhood composition and informal social control actions.

THE SPATIAL DYNAMICS OF CRIME AND INFORMAL SOCIAL CONTROL

Early studies of social disorganization theory revealed that not only did crime cluster in particular neighborhoods, these neighborhoods were often adjacent to each other, sharing similar socio-demographic characteristics (Shaw and McKay, 1942). Contemporary research reveals the same patterns - disadvantaged neighborhoods with high levels of violence are often proximate to other disadvantaged, high crime areas (Mears and Bhati, 2006; Morenoff, Sampson and Raudenbush, 2001; Peterson and Krivo, 2010; Sampson, 2012; Tita and Greenbaum, 2009). In their study of resource deprivation and homicide, Mears and Bhati (2006) find that the spatial proximity of disadvantage is more consequential for homicide in the focal neighborhood than the level of homicide in nearby communities. They conclude that the "spatial diffusion mechanism often found in the homicide literature could be an artefact of omitting the spatially lagged resource deprivation measure" (Mears and Bhati, 2006: 528). Similarly, Boessen and Hipp (2015) find that concentrated disadvantage in the block group and area surrounding the block group has a positive relationship with crime in the focal block, especially violent crime.

Cross-sectional studies suggest that the ecological conditions of nearby areas also influence regulatory processes in focal neighborhoods. In the U.S., collectively efficacious neighborhoods have low levels of violence and are spatially proximate to other neighborhoods with low levels of violence, reasonable levels of affluence and low levels of mobility and ethnic/racial concentration (Morenoff, Sampson and Raudenbush, 2001; Sampson, 2012; Sampson, Morenoff and Earls, 1999). Conversely, neighborhoods with low levels of collective efficacy are closer to disadvantaged neighborhoods with high levels of violence, residential mobility and racial/ethnic concentration. Although "concentrated disadvantage, crime and collective efficacy are spatially interrelated in ways that go beyond chance expectations" (Sampson, 2012: 240), there is no study that we are aware of that considers how the socio-demographic context of both nearby and focal neighborhoods influence changes in informal social control actions and consequently crime. Understanding these spatial and temporal associations is therefore a key goal in our research.

THE PRESENT STUDY

As there are so few longitudinal, ecologically focused studies designed to test the core tenets of social disorganization theory and its reformulations, we do not know whether or not neighborhood ties lead to shared expectations for informal social control; if neighborhood ties and shared expectations for informal social control influence the exercise of informal social control; and if the exercise of informal social control influences crime over time. Further, we have limited knowledge of how compositional shifts across neighborhoods in cities undergoing significant change influence crime and the effects of increasing crime on neighborhood regulation over time. Studies have demonstrated that changes in the socio-demographic context influence crime at a later time point (Friedson and Sharkey, 2015; Sampson, 2012) and conversely, that crime has the capacity to change neighborhood residential stability and disadvantage (Boggess and Hipp, 2010; Dugan, 1999; Hipp, 2010a; Hipp, 2010b; Hipp, Tita and Greenbaum, 2009; Morenoff and Sampson, 1997; Taylor, 1995; Xie and McDowall, 2008). Yet they do not reveal whether this relationship is attributable to neighborhood informal social control.

Responding to a call to better understand these relationships (Bellair and Browning, 2010; Kubrin, 2008), we address these limitations in social disorganization scholarship in the following ways. First, we empirically test whether or not the neighborhood composition directly influences the development of neighborhood social ties, shared expectations for informal social control and the actual behaviors undertaken by local residents that may prevent crime as social disorganization theories would predict (Bursik and Grasmick, 1993; Sampson, 2012; Sampson, Raudenbush and Earls, 1997). In line with social disorganization research, we expect that disadvantage, ethnic heterogeneity and residential mobility will weaken all three measures of informal social control. Second, we assess if the presence of ties, shared expectations and actions influence changes in violent, property and drug related crime at a later time point. Here we extend the earlier work of Hipp and Wickes (2017) by focusing on the specific mechanisms identified in social disorganization theory (ties, expectations and actions) and whether these mechanisms have similar or different effects on our three crime types. Based on the work of Sampson and others (1997) and the recent work of Hipp and Wickes (2017), we predict that neighborhoods with residents who actually engage in problem solving behaviors will experience lower violent, property and drug related crime. (Sampson 2012; Sampson, Raudenbush and Earls 1997). Next, as our approach also replicates the work of Hipp and Steenbeek (2016), we determine if crime is the catalyst for changes in informal social control and/or the compositional structure of neighborhoods. We contend that crime will lead to increases in disadvantage, residential stability and the concentration of ethnic minorities, which in turn will reduce informal social control (Hipp and Wickes, 2017). Finally, as neighborhoods are "embedded rather than isolated socio-spatial units" (Taylor, 2015:108), we extend the social disorganization research by examining the socio-demographic changes in nearby and focal neighborhoods and their association with informal social control and crime over time. This allows us to test if the neighborhood composition generates informal social control and therefore impacts crime levels, versus the extent to which there is a broader spatial pattern whereby the characteristics of surrounding neighborhoods have an additional impact. Specifically, given the pattern of spatial economic segregation, we posit that nearby areas of disadvantage will have a reinforcing positive effect on crime (Chamberlain and Hipp, 2015). We have less reason to expect the other structural measures of neighborhoods to exhibit such broader spatial patterns, although we nonetheless test this here.

We conduct our analyses using survey data from 148 neighborhoods in a major capital city in Australia. Australia is closely linked with the U.S., Canada, Germany, the United Kingdom and other OECD countries in its trade linkages, legal structures, technological advances and economic cycles (Otto, Voss and Willard, 2001). Brisbane, our research site, is located in South East Queensland and is Australia's third largest city with an estimated population of over 2 million people covering approximately 15,000 square kilometers. It has a monocentric urban form through which a major river divides the northern and southern areas of the city. In the last two decades it has undergone significant and rapid change. Population growth has increased and the composition of the immigrant population has changed significantly in a relatively short period of time (Australian Bureau of Statistics (ABS), 2013; Hugo, Feist and Tan, 2013), with the majority of recent immigrants coming from India and China and humanitarian refugees from Afghanistan, Sudan and Somalia (Hugo, 2011). Income inequality has also increased in the last two decades (Fenna and Tapper, 2015; Fletcher and Guttmann, 2013) and disadvantage has become more concentrated (Baum and Gleeson, 2010). Like all cities internationally, crime is not distributed evenly or randomly across Brisbane. While violence is relatively rare in areas located outside of key entertainment precincts, particular areas experience higher levels of property crime and nuisance offences than others (Queensland Police Service, 2015). Our research site therefore allows a thorough examination of the core tenets of social disorganization theory and, as importantly, can demonstrate the interplay between neighborhood compositional change, informal social control and crime in a city experiencing social and economic shifts.

METHODS

THE AUSTRALIAN COMMUNITY CAPACITY STUDY (ACCS)

In our analyses we utilize survey data from waves 2, 3 and 4 (2007, 2010, 2012) of the Brisbane ACCS survey.[4] The ACCS is a longitudinal study of urban neighborhoods in Brisbane concerned with understanding the spatial and temporal dynamics of community regulation and benchmarking the effects of these community processes on social problems against the international neighborhood effects literature. The ACCS is comparable to several studies, in particular the Project for Human Development in Chicago Neighborhoods (PHDCN), that examine informal social control and a range of social problems (Sampson, Raudenbush and Earls, 1997; Sampson and Wikstrom, 2008; Steenbeek and Hipp, 2011).

The ACCS Brisbane survey site comprises 148 randomly drawn neighborhoods[5] from a possible 429 neighborhoods in the Brisbane Statistical Division. The average population of the ACCS neighborhoods is about 6,000 (for further information on the ACCS study design please see http://www.uq.edu.au/accs). The ACCS sample is non-contiguous. The administrative boundaries of these neighborhoods are somewhat larger than census tracts in the U.S., where the average size of the census tract is approximately 4,000 inhabitants. Yet we note that research examining the effects of neighborhood processes and crime have relied on much larger units of analysis, for example Sampson and his colleagues employed neighborhood clusters with an average size of 8,000 residents (Sampson, 2012; Sampson et al., 1997).

SURVEY PROCESS AND PARTICIPANT SAMPLE

The ACCS surveys were conducted by the Institute for Social Science Research at the University of Queensland using computer-assisted telephone interviewing to administer the survey to residents aged 18 years or over who were usually resident in private dwellings with telephones in the selected neighborhoods in Brisbane[6]. Particular focus was placed on contacting those who had participated in previous waves (see Appendix 1). All participants were randomly selected using random digit dialing. At each data collection period, power

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[4] Wave 1 used an alternate geographic unit of analysis that is not comparable to those in the later waves.
[5] In Australia, the term "suburb" is used to refer to a feature that in the U.S. would be referred to as a "neighborhood". Throughout, we use the more familiar term "neighborhood" to refer to these. The suburbs in the ACCS sample include those that are adjacent to the main city center and those located in peri-urban areas which have experienced large increases in population growth.
[6] In Australia, the number of mobile phone only users has only increased recently. 90% of the population was covered by landline phones in 2008, and in 2011 (the last wave of our sample) the number of mobile phone-only users was estimated to still be just 19% (Australian Communications and Media Authority, 2012).

analyses using Optimal Design Software for multi-level samples determined the number of residents needed per neighborhood to maintain ecometric reliability.

Response rates over the three waves ranged from 36% to 43%, and cooperation rates ranged from 46% to 62%. In contrast to face to face surveys like those used in the PHDCN or the Los Angeles Family and Neighborhood Study, phone response rates tend to be lower, yet the response rates for ACCS are similar or higher than other phone-based studies in Australia and the U.S. (Duncan and Mummery, 2005; Lai, Zhao and Longmire, 2012; Larsen et al., 2004; Pickett et al., 2012; Wood, Giles-Corti and Bulsara, 2012). The ACCS sample is representative of the census across several socio-demographic indicators; however, home owners (65.3% 2011 census vs 87.9% ACCS Wave 4), married residents (47.3% 2011 census vs 66.6% ACCS Wave 4), university educated (13.7% 2011 census vs 33.9% ACCS Wave 4), and those who have not recently moved (37.6% 2011 census vs 17.1% ACCS Wave 4) are over-represented in the ACCS sample. Information on the final sample composition is provided in Appendix 3.

ADDITIONAL DATA SOURCES

In this study we use Australian Bureau of Statistics (ABS) census data from 2006 and 2011. Census data include a range of empirically derived variables from the neighborhood effects literature (Bursik, 1988; Sampson, Raudenbush and Earls, 1997; Shaw and McKay, 1942). As the Australian Geographical Classification System changed substantially at the 2011 census, the ACCS team contracted the ABS to provide all census data concorded to the 2006 census boundaries, allowing for geographical consistency across our time periods.

The Queensland Police Service (QPS) provided crime incident information aggregated to the neighborhood level for the Brisbane area. QPS crime incident data represents counts of reported offences in all neighborhoods in South-East Queensland from 2005 to 2013.

DEPENDENT VARIABLES

We employ monthly QPS crime incident data for measures of violent crime, property crime and drug crime. Violent crime includes homicide, manslaughter, attempted murder, conspiracy to murder, assaults (excluding sexual) and robbery. Property crime includes unlawful entry, theft, stealing, arson, handling stolen goods, property damage and unlawful use of a motor vehicle. Drug crime includes trafficking, possession, production, and supply of dangerous drugs. These measures are drawn from official crime reports to the police, and are reported as rates per 1,000 persons. We used rates averaged over the two years nearest the wave of the survey to smooth out yearly fluctuations in crime rates.

INDEPENDENT VARIABLES

For our main analytic models, the neighborhood independent variables include measures of *neighborhood social ties* and *expectations for informal social control* and *the exercise of informal social control*. These measures contain items that are identical to those used in the PHDCN and represent the core neighborhood processes identified in social disorganization theory, the systemic model of community regulation and collective efficacy theory.

The items that comprise our measure of *neighborhood social ties* ask residents to comment on how often you and people in your community (never; rarely; sometimes; often): 1) do favors for each other; 2) visit in each other's homes or on the street; and 3) ask each other advice about personal things such as child rearing or job openings. These items represent parochial social ties and depict what Woldoff (2002: 97), classifies as "more intense neighbor relationships" or what Sampson (2013) refers to as active neighborhood ties. The individual level scale reliability for these items is $\alpha = 0.76$ and the neighborhood reliability is

$\alpha = 0.58$. Approximately 5 percent of the variation in neighborhood ties is between neighborhoods.

Our neighborhood level measure of *expectations for informal social control* includes the same items used to measure informal social control in the original study of collective efficacy (Sampson, Raudenbush and Earls, 1997). They ask residents to assess how likely it would be that neighbors would do something about: a group of community children skipping school; children spray painting graffiti; a fight; a child showing disrespect; and the fire station closing down (response categories were very likely, likely, unlikely and very unlikely). These items are reliable at both the individual ($\alpha = 0.64$) and neighborhood ($\alpha = 0.82$) level. Approximately 14 percent of the variation in this measure is between neighborhoods.

Our final measure represents the *exercise of informal social control*. Again items for this variable are identical to those included in the PHDCN. They comprise a scale of three items asking whether or not participants engaged in a range of actions (attended a meeting, signed a petition and worked with neighborhood residents to solve a local problem) in the last 12 months. These items form a reliable scale at the individual ($\alpha = 0.61$) and neighborhood ($\alpha = 0.70$) level, and approximately 6.5 percent of the variation in this measure is between neighborhoods.

Summary statistics for all variables are shown in Table 1. Correlations among variables across all waves are similar, thus we present Wave 4 correlations in Appendix 2.

<<Table 1 here >>

All variables in our analytic models based on survey responses – neighborhood social ties, expectations for informal social control and the exercise of informal social control - were adjusted for individual-level biases by accounting for compositional effects in which neighborhood assessments may be systematically affected by the characteristics of respondents in the neighborhood. These measures represent factor scores at the individual level derived from a maximum likelihood factor analysis, and then standardized factor scores were constructed with mean of 0 and standard deviations of 1. We next estimated fixed effects models in which the outcome measures were the previously computed factor scores, and included indicator variables for all neighborhoods, as well as several individual characteristics that might systematically bias perceptions. We then used the estimated coefficients for each of the neighborhoods from this analysis as unbiased estimates of the neighborhood construct in the models.[7]

Drawing on the social disorganization literature, we included several neighborhood compositional variables based on census data from the ABS. We constructed a measure of *residential instability* as the percentage new residents in the last five years. *Concentrated disadvantage* was constructed as a factor score combining three measures: median household income; unemployment rate; percent one parent households. A measure of *ethnic heterogeneity* was constructed as a Herfindahl index based on nine most common language groups[8]. To capture those in the prime offender age group, we constructed a measure of the *percent aged 15 to 24.*

ANALYTIC APPROACH

Considering the longitudinal nature of the data, we estimated cross-lagged simultaneous equation models (Finkel, 1995). We account for possible autocorrelated errors over time by allowing correlations between the error terms for each outcome variable in adjacent time periods, and allowing correlations between the error terms of the outcome variables at the same time point. Given the temporal lagging of the measures, these models

[7] The following individual level variables are included: household income, education level, length of residence in the neighborhood, female, age, homeowner, marital status (single, widowed, divorced, and married as the reference category), presence of children, and speaking only English in the home. Previous research found very high correlations between measures using a frequentist approach, as we do here, and those using a Bayesian approach (see Steenbeek and Hipp, 2011, footnote 12 on page 846).

[8] This measure was based on the following language groups: indigenous; East Asian; South-central Asian; Southeast Asian; Southern Asian; Eastern European; Northern European; Southern European; other languages.

are identified (for a discussion of identification of such models, see Finkel 1995). We account for changing levels of the outcome variables over time by estimating a unique intercept value at each time point. For each outcome variable, the equation is:

$$(1) \qquad y_{1t} = \alpha_t + B_1Y_{t-1} + B_2WY_{t-1} + B_3X_{t-1} + \varepsilon_{1t}$$

where y_{1t} is the variable of interest being explained (say, the violent crime rate) which is measured at time *t*, α_t is an intercept at each time point, Y_{t-1} is a matrix of the endogenous variables in the model measured at the previous time point, B_1 is a vector that captures the effect of these other measures on the violent crime rate, WY_{t-1} is a matrix of spatially lagged variables at the previous time point and B_2 is a vector of parameters that capture their effects on the respective crime rate, X is a vector of other control variables in the model at the previous time point which have a B_3 effect, and ε_1 is an error term with an assumed normal distribution. As we have three survey waves (t=1-3), the equation for the outcomes of neighborhood social ties, expectations or exercise of informal social control expectations, and crime appear twice (they cannot be estimated for the first wave as there are no t-1 observations at that point), and the three measures from the census appear once. Figure 1 demonstrates the model for three endogenous variables; we limit this figure to three variables for interpretability (the model simply generalizes from this figure). As can be seen there, an outcome at the next time point (say the crime rate), is a function of the crime rate at the previous time point and the other measures in the model at the previous time point. The correlated residuals are shown in this figure.

<<<Figure 1 about here>>>

In addition, given possible concern that our two-year lag is too long a period of time to capture the relationship between informal social control and crime, we also estimated an ancillary set of models that estimated the relationship between these variables at the same time point. These models use the same variable at the previous time point as an instrumental variable for identification. Thus, whereas our main models posit that the level of our variables of interest at the previous time point impact the change in the outcome variable over the next two years, these alternative models instead posit that there is a simultaneous relationship between informal social control and crime at a point in time. An important assumption of this model that allows these lagged variables to serve as instrumental variables is that whereas the level of informal social control at the previous time point impacts the level of informal social control in the current time period, it has no additional impact on the level of crime beyond the effect that the current level of informal social control has. Although we believe it is unlikely that this relationship would occur over such a non-specific time period (both short-term and long-term), this nonetheless should be kept in mind as a limitation of this model.

To account for spatial lag effects, we first created a spatial weights matrix in which each neighborhood was linked to all neighbors within 5 miles (weighted by an inverse distance decay), and then computed spatially lagged measures by multiplying the values of key measures in these neighborhoods by this weight matrix (row standardized). We constructed spatial measures of the census variables and the crime rates; we were not able to construct spatial measures of the survey variables as the sampling strategy does not allow obtaining estimates of surrounding neighborhoods. We then temporally lagged these spatially lagged measures, which mirrors the approach adopted by other studies (Hipp, Tita, and Greenbaum 2009; Steenbeek and Hipp 2011). Our models demonstrated satisfactory overall approximate fit, as reported at the bottom of Tables 2-4: although the chi-square result was significant, indicating a lack of perfect fit, the root mean squared error of approximation (RMSEA) values were generally at or below a recommended cutoff of .10, and the Confirmatory Fit Index (CFI) values were generally well above .90. We assessed possible collinearity in our equations and found no evidence, as the variance inflation values were all below 5, well below a recommended cutoff value of 10 (Kennedy 1998).

RESULTS

FEEDBACK EFFECTS ON STRUCTURAL MEASURES

We begin by focusing on the possible feedback effects of crime and other measures on neighborhood structural characteristics as part of the violent crime model (see Table 2).[9] Looking first to what explains the level of disadvantage at the next time point, we see that higher levels of disadvantage at the prior time point are associated with higher levels of disadvantage at the current time point, as expected (b =0.726, p<.01). This is a stasis effect that is observed for all of the equations in our model: the level of the measure at one time point is positively related to the level at the next time point. There is also a modest positive effect of the level of concentrated disadvantage in the surrounding area ($p < .10$). As revealed in Hipp and Wickes' (2017) study, we also see a feedback effect from violence to disadvantage, as higher levels of violence in the neighborhood at one time point are associated with higher levels of disadvantage at the next time point (b = 0.545, p<.01). However, our measures of informal social control have no relationship with levels of future disadvantage.

<<Table 2 here >>

In the equation predicting levels of residential instability at the next time point, none of the other compositional features of the focal neighborhood or surrounding areas are related to subsequent instability. Interestingly, the exercise of informal social control at one point was associated with higher levels of residential instability at the next time point (b = 10.198, p<.05). As Brisbane has developed considerably over a relatively short period of time, the exercise of informal social control may have increased in these areas as the neighborhood began to change and grow. There was also modest evidence that neighborhoods with more social ties at a one point in time (or surrounded by more residential stability) experience greater residential stability at a later time point, though these relationships do not reach conventional significance ($p<.10$). No other variables in this equation were significant.

Although higher levels of violence do not lead to more ethnic heterogeneity at the next time point, several of the socio-demographic measures are important. Neighborhoods with more residential instability at one time point (b = 0.001, p<.05) have higher levels of ethnic heterogeneity at the next time point, suggesting that this general instability also leads to turnover in the ethnic composition of the neighborhood. There is also a spatial effect as neighborhoods surrounded by higher levels of ethnic heterogeneity experience larger increases in ethnic heterogeneity by the next time point (b = 0.561, p<.01). It is also the case that neighborhoods surrounded by higher levels of disadvantage experience higher levels of ethnic heterogeneity at the subsequent time point (b = 0.018, p<.01). Whereas greater instability in the neighborhood itself leads to subsequently higher levels of ethnic heterogeneity, greater instability in the surrounding area actually results in lower ethnic heterogeneity at the next time point (b = -0.003, p<.05). These relationships between neighborhood demographics mirror those found in Hipp and Wickes' (2017) longitudinal study of collective efficacy and violence. Finally, neighborhoods with more social ties have lower levels of ethnic heterogeneity at the next time point (β = -0.106, p<.01).

EXPLAINING INFORMAL SOCIAL CONTROL OVER TIME

We next ask what explains the level of neighborhood social ties, expectations of informal social control, and the exercise of informal social control. We see neighborhoods that exercise informal social control at one point in time actually have greater numbers of

[9] We estimated our models with and without spatial effects. We found few substantive differences in the relationships between our variables when only considering the composition of the focal area. As others have argued the importance of the compositional features of nearby areas, we focus on the results with spatial lags.

neighborhood social ties at the subsequent time point (b = 0.146, p<.01). Thus, informal social control action may generate social ties. Ethnic heterogeneity, instability and disadvantage are not associated with the development of neighborhood ties over time.

We do see evidence consistent with systemic theory that neighborhoods with more social ties have higher expectations of informal social control at the next time point (b = 0.085, p<.05). An interesting result is higher levels of informal social control action are associated with higher levels of shared expectations for informal social control at the next time point (b = 0.83, p<.05), suggesting a virtuous feedback cycle and updating of expectations (Hipp, 2016). In line with Hipp and Wickes' (2017) findings, our results provide relatively strong evidence that concentrated disadvantage is deleterious for shared expectations for informal social control, as neighborhoods with more concentrated disadvantage (b = -0.036, p<.01), and those surrounded by more disadvantage (b = -0.018, p<.01) have reduced expectations for informal social control at the next time point. Further, higher levels of residential instability in the surrounding area has a negative relationship with subsequent expectations for informal social control (β = -0.003, p<.05).

Regarding the exercise of informal social control, we find fewer significant effects. There was no association between neighborhood social ties and informal social control expectations. Further, whereas we find that the exercise of informal social control is associated with higher expectations of informal social control at the next time point, this relationship is not reciprocal. The implicit assumption of collective efficacy theory that expectations will lead to the exercise of informal social control at the next time point is not borne out in our study. However, some neighborhood structural characteristics appear important. Higher levels of concentrated disadvantage in the surrounding area are associated with less exercise of informal social control (b = -0.032, p<.01). There is evidence that higher levels of neighborhood ethnic heterogeneity (b = 0.173, p<.10) and surrounding area residential instability (b = 0.007, p<.01) are associated with increases in the exercise of informal social control at a later time point. These findings provide little support for the proposition that neighborhood social ties lead to expectations for informal social control and subsequently the exercise of informal social control. Actions, at least in the context of violent crime, appear necessary for developing shared expectations for action, yet neither ties nor expectations influence actions over time.

The final equation of this table reports the predictors of violence over time. Here we see that neighborhoods with higher levels of concentrated disadvantage at one time point have higher levels of violence at the next time point (b = 0.057, p<.01) (see also Hipp and Wickes, 2017) and, higher levels of residential instability in the focal (b = -0.003, p<.05) and nearby neighborhood (b = -0.006, p<.10) are actually associated with *lower* levels of violence at the next time point. Although there is not a significant relationship between expectations for informal social control and violence at the next time point, it is interesting to note that neighborhoods that exercise greater informal social control at one point in time have somewhat lower violence in the future (b = -0.133, p<.10). Neighborhoods with more social ties did not differ from other neighborhoods in the level of violence over time. We revisit these findings in the discussion.

Mechanisms of drug crime

As we are interested in whether or not informal social control processes operate similarly across crime types, in Table 3 we estimate a similar model for drug crime. We first focus on whether the level of drug crimes in a neighborhood differently impacts any of these outcomes compared to the level of violent crime in the previous model. Nearly all of the results were the same. Neighborhoods with higher levels of residential instability have lower levels of drug crime at the next time point (b = -0.010, p<.01). In line with the negotiated coexistence model (Browning et al., 2004) and Pattillo's (1998) study of Groveland, we find that higher levels of neighborhood ties (b=0.56, p<.01) are associated with higher levels of drug crime at the next time point. Conversely, neighborhoods with higher levels of expectations for informal social control have fewer drug crimes over time (b=-.96, p<.01). This suggests that informal social control may work differently for the regulation of different types of crime. We revisit these findings in the discussion section.

<<Table 3 here>>

Mechanisms of property crime

Our final model substitutes the property crime measure as the crime measure (see Table 4). In the equations in which property crime is a covariate predicting the other outcome variables, the results are similar as those for the violent crime model reported in Table 2. One exception is that neighborhoods with more property crime at one point in time actually have more social ties at the subsequent time point, suggesting that this type of crime might actually encourage bonding among residents. In the equation where property crime is the outcome measure, we see that unlike violent crime, neighborhoods with more social ties at one time point experience modest increases in property crime at the next time point (b = 1.046, p<.10).

<<Table 4 here>>

Sensitivity tests: Assuming simultaneous effects

One possible criticism is that although our cross-lagged models assume that the levels of collective efficacy or neighboring at one point in time reduce the amount of crime experienced over the next two years, the causal process may operate over a shorter time period (Hipp and Wickes, 2017; Taylor, 2015). If this is the case, this requires estimating simultaneous equations given the limited temporal resolution of our data. It also necessitates the use of instrumental variables, and we use the measure of interest at the prior time point as the instrument to identify each equation.

In short, the pattern of results in these simultaneous models is very similar to that observed in the cross-lagged models. There is no evidence across these three crime types that the presence of more neighborhood social ties, perceived informal social control, or the exercise of social control are associated with reduced crime. In the violent crime model, the relationship between the exercise of informal social control and violence is weaker than in the cross-lagged model. In the drug crime model, the negative relationship between perceived informal social control and drug crime is weaker. The complete results are presented in Tables A4, A5, and A6 in the Appendix.

DISCUSSION

The central propositions underpinning traditional and contemporary social disorganization theories state that (1) neighborhood composition impacts informal social control (2) informal social control influences levels of crime and (3) these relationships should hold for different types of crime. In the broader neighborhood effects literature, there is further suggestion that these relationships reinforce each other over time and that crime is influenced by the socio-demographic context of nearby areas. In this paper, we tested each of these claims and our results reveal three main findings.

First, we find strong reciprocal relationships between changes in neighborhood composition and informal social control. Disadvantage, ethnic heterogeneity and residential mobility have increased and concentrated over time in ACCS neighborhoods and these changes have consequences for the three components of informal social control. Neighborhoods with higher levels of concentrated disadvantage experience decreases in shared expectations for informal social control over time, and neighborhoods surrounded by higher levels of disadvantage have fewer people exercising informal social control. This supports cross-sectional studies showing the deleterious impact of disadvantage on informal social control (Bursik and Grasmick, 1993; Sampson, 2012; Shaw and McKay, 1942) and demonstrates the importance of considering city wide dynamics and their influence on specific neighborhood processes. Interestingly, we find that higher levels of ethnic heterogeneity increase the exercise of informal social control in the future, and these actions also lead to increased residential mobility. When people are dissatisfied with changes in their local neighborhood, they can either leave the neighborhood if resources are available, or they can exercise 'voice', which can involve a range of different actions targeted towards keeping the 'quality' of their neighborhood intact (Wilson and Taub, 2006). For example, in their qualitative case study of Beltway, Chicago, Wilson and Taub (2006) found that local residents would rally against policies that made it easier for Latinos and African Americans to relocate in their neighborhood. It is also possible that residents might exercise voice *and* relocate if their voice has limited impact. Although our data do not allow us to expressly test this assumption, we argue this is a plausible explanation for our results and one that requires further study.

Our second finding is that the relationships between our three components of informal social control and crime do not necessarily correspond with the tenets of social disorganization theory. In all models, higher levels of neighborhood social ties lead to stronger expectations for informal social control over time, which aligns with theory and cross-sectional research in the U.S. (Bursik and Grasmick, 1993). Yet neighborhood social ties and shared expectations for informal social control do not lead to the *exercise* of informal social control. What residents do in response to neighborhood problems is not a function of these proposed theoretical mechanisms. However, the exercise of informal social control at an earlier time point does lead to greater neighborhood ties in the future. This is interesting.

Whereas most cross-sectional studies of collective action find that neighborhood social ties are associated with a range of civic behaviors or community group membership (Oliver, 1984), others argue that ties are insufficient for action and that action is likely the result of efficacious individuals, or efficacious neighborhoods with sufficient social resources (Bandura, 1997; Sampson, Raudenbush and Earls, 1997). Our results suggest that participating in a community oriented endeavor may be a critical step in the *formation* of neighborhood ties. This has theoretical implications for the systemic model of community of regulation. Neighborhood social ties may exist for some people in some neighborhoods, but these social ties may not be sufficient for conveying shared expectations for social control. Nor do they necessarily prompt the exercise of informal social control as we find here. Instead it is what residents *do* in the context of their neighborhood that reinforces norms and a shared neighborhood identity. This *doing* is what brings together a group of otherwise disconnected urban dwellers.

The third and most significant finding of our research indicates that neighborhood ties, expectations for action and the exercise of informal social control do not operate to reduce crime as theorized in contemporary and traditional social disorganization theories and, moreover, have different effects on crime depending on the crime type. For example, we find strong neighborhood ties lead to higher levels of drug crime over time, even though expectations for informal social control are associated with lower drug crime rates over time. Pattillo's (1998) study of crime in Groveland provides a rich account of neighborhood social ties and their association with informal social control. Pattillo's (1998) grounded model of neighborhood social control demonstrates how long held social ties serve to reinforce norms against law violation but simultaneously allow a certain amount of law violation within the network. Pattillo (1998) further argues that long term, established neighborhood social ties connect law abiding and law violating people. These overlapping networks have consequences for the informal social control of crime as “the more people are familiar with one another, the more illicit networks are absorbed into mainstream connections and thereby normalized” (Pattillo, 1998: 763). This “paradox of social organization” (Browning, Feinberg and Dietz, 2004) appears to hold in our longitudinal study of social disorganization theory, at least for drug related crimes.

Further, and in contrast to cross-sectional studies of collective efficacy and violence in Australia and the U.S. (Mazerolle, Wickes and McBroom, 2010; Sampson, Raudenbush and Earls, 1997), informal social control expectations actually are associated with *higher* violence in the subsequent period. We offer two explanations for this. First these findings point to the ‘dark side’ of informal social control, which is not considered in collective efficacy scholarship. In violent communities, informal social control may not always be pro-social in nature. Indeed, is possible that violence promotes anti-social informal social control responses as depicted in case studies of violent urban neighborhoods (Anderson, 2000). The items we use to measure expectations for informal social control are the exact items used in the PHDCN survey. They simply ask whether or not the respondent believes that other people in the community will do something when faced with various problems. In neighborhoods where violence is high, violence can be used as a form of informal social control to resolve disputes or grievances (Anderson, 2000; Black, 1983). This would be particularly true in neighborhoods where residents have little trust in the police (Black, 1983; Kubrin and Weitzer, 2003) and there is some evidence that might be the case in the Australian context (Sargeant, Murphy, Wickes and Mazerolle, in press). The second explanation relates to our use of official crime data. As we employ police incident data in our analyses, an alternative argument is that higher violence at the next time might instead reflect higher reporting and/or police crackdowns. Our data do not allow us to explicitly test this, but we recognize this is as a possible explanation for this finding.

Also contrary to the social disorganization literature, what residents do in response to problems had no effect on property or drug crime at the next time point in our analyses. For these crime types, resident actions taken in response to neighborhood problems do not translate into lower subsequent crime rates. In our sample, “the micro-social control” of unwanted behavior (Bursik, 1999: 85) does not significantly alter macro changes in property and drug crime (Matsueda, 2013; Taylor, 2015). This challenges one of the key propositions in social disorganization theory (including its more recent reformulations) – that the exercise of informal social control is the most proximate mechanism for controlling crime.

The lack of support for a link between the exercise of informal social control and crime then begs two questions. The first asks if there are possible cross-cultural differences in the regulation of crime between the U.S. and Australia. There is no evidence from cross-sectional research to suggest this is the case. The relationship between collective efficacy and crime in Australia is strikingly similar to the relationship found in Chicago (Mazerolle et al., 2010; Sampson et al., 1997). While some studies have looked at collective efficacy at one time point and assessed its impact on crime at a later time point (Morenoff et al., 2001; Sampson et al., 1997), there are no studies in the U.S. that quantitatively and longitudinally examine the association between the reported actions residents take in response to local problems and their link to crime at a later time point. Though our findings align with results from a similar longitudinal study in the Netherlands (Hipp and Steenbeek, 2016; Steenbeek and Hipp, 2011), we simply do not know if results differ substantially from the U.S. context. Replication of this research in the U.S. is needed to shed further light on this relationship. The second is whether the exercise of formal social control is simply more predictive of crime rates than residents’ actions. Our study focusses exclusively on relationships among residents and residents’ own reported actions. Nearly thirty years ago Bursik (1988) lamented the absence of formal organizations in social disorganization research, yet outside of neighborhood case studies, there is a dearth of scholarship that simultaneously considers the *actions* of citizens and the *actions* of formal organizations and their associations with crime. Such a project would be hugely ambitious and cost/time prohibitive. We know that organizations have different objectives that promote prosocial or anti-social behavior (Kubrin and Hipp, 2014; Wo, 2014) and organizations like the police are likely to evoke different strategies at different times that significantly impact crime rates. As we mention earlier, crack downs on drug crimes or gang related activities may lead to increases in officially recorded crime data. Thus, it is entirely possible that formal social control trumps the influence of citizen initiated actions in explaining the variation of crime across neighborhoods.

We acknowledge some limitations. Although our study uses longitudinal data, there are assumptions in our modeling strategy. The cross-lagged models assume that the time period in which the causal effect occurs is two years later. This may be too long, and we therefore also estimated models in which we assumed a much shorter time period (but these relied on assumptions about our instrumental variables). Another issue is that our study is also unable to identify more subtle acts of informal social control, which may be important in preventing crime. Warner (2007) notes a wide range of actions taken by local residents in response to unwanted behavior (see also Greenburg and Rohe, 1986; Reynald, 2009). These actions include chastisement and criticism of others, gossip among neighbors and withdrawal of social support for those who are violating agreed upon norms. The success of these everyday forms of informal social control may be more effective in preventing or reducing crime, yet no study has systematically examined these ordinary actions and their association with crime over time. We believe this is a critically important area for future research.

In summary, our study provides a temporal ordering test of social disorganization theory. As our research site is similar to the U.S. and other western democratic countries in terms of urban design, and political and economic structures (Otto, Voss and Willard, 2001), our results have consequences for understanding the associations between neighborhood composition, informal social control and crime. We find that disadvantage and crime have a reciprocal and deleterious relationship, and disadvantage has a negative influence on shared expectations for informal social control. Yet our analyses reveal that the exercise of informal social control actions is not strongly associated with crime across time. Further, neighborhood social ties and shared expectations for informal social control do not influence the exercise of informal social control (Bursik and Grasmick, 1993; Sampson, 2012). Instead, it appears that informal social control action results in increased social ties in neighborhoods and a perception of collective efficacy (Hipp, 2016). Taken together, these findings challenge traditional and contemporary social disorganization theories, raise important questions relating to the efficacy of citizen initiated actions in preventing crime, and highlight important avenues for future social disorganization research in Australia and elsewhere.

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TABLES and FIGURES

Table 1. Summary statistics for ACCS survey items (waves 2, 3 and 4), census variables (2006 and 2011) and QPS crime data.

	Wave 2		**Wave 3**		**Wave 4**	
	Mean	SD	Mean	SD	Mean	SD
Property Crime	5.24	5.39	4.05	4.31	4.95	4.88
Violent Crime	0.45	0.63	0.38	0.52	0.39	0.55
Drug Crime	1.08	1.96	0.80	1.29	0.90	1.31
Neighborhood Social Ties	0.01	0.18	0.02	0.19	0.02	0.19
Informal Social Control Expectations	0.01	0.14	0.02	0.16	0.01	0.17
Exercise of Informal Social Control	0.00	0.19	0.01	0.17	0.00	0.18
Concentrated Disadvantage	0.00	1.00	0.00	1.00	0.00	1.00
Ethnic Heterogeneity	0.18	0.10	0.18	0.10	0.12	0.11
Residential Instability	42.30	8.91	42.30	8.91	38.17	10.29
Percent Aged 15 to 24 Years	13.97	2.83	13.97	2.83	14.03	2.88

Table 2. Results of cross-lagged simultaneous equations for violence

	Disadvantage	Residential instability	Ethnic heterogeneity	Neighborhood Social Ties	Informal Social Control Expectations	Exercise of Informal Social Control	Violence
Prior disadvantage	0.726 **	0.739	0.008	0.000	-0.036 **	0.012	0.057 **
	(16.86)	(0.84)	(1.25)	-(0.03)	-(4.26)	(1.13)	(3.62)
Prior residential instability	0.002	0.788 **	0.001 *	0.000	0.000	0.000	-0.003 *
	(0.47)	(11.49)	(2.54)	(0.30)	(0.76)	-(0.08)	-(2.29)
Prior ethnic heterogeneity	-0.111	-9.838	0.528 **	0.000	-0.019	0.173 †	-0.102
	-(0.32)	-(1.38)	(10.60)	(0.00)	-(0.32)	(1.91)	-(0.80)
Prior percent of residents aged 15 to 24 years	0.008	0.244	0.005 *	-0.015 **	-0.003	-0.003	0.002
	(0.61)	(0.88)	(2.45)	-(3.91)	-(1.04)	-(0.81)	(0.37)
Nearby concentrated disadvantage	0.072 †	0.235	0.018 **	-0.008	-0.018 **	-0.032 **	-0.003
	(1.88)	(0.30)	(3.32)	-(0.79)	-(2.67)	-(3.19)	-(0.24)
Nearby residential instability	-0.005	0.308 †	-0.003 *	0.000	-0.003 *	0.007 **	-0.006 †
	-(0.58)	(1.66)	-(2.29)	-(0.06)	-(1.98)	(2.93)	-(1.75)
Nearby ethnic heterogeneity	-0.532	1.093	0.561 **	-0.267 †	-0.136	-0.001	-0.074
	-(0.96)	(0.10)	(7.02)	-(1.72)	-(1.39)	-(0.01)	-(0.36)
Nearby percent residents aged 15-24 years	-0.031 *	0.230	0.002	0.003	0.004	-0.001	0.007
	-(2.00)	(0.74)	(1.06)	(0.70)	(1.34)	-(0.29)	(1.16)
Prior neighborhood social ties	-0.083	-8.325 †	-0.106 **	0.475 **	0.085 *	0.055	0.062
	-(0.38)	-(1.88)	-(3.42)	(6.50)	(2.19)	(0.90)	(0.72)
Prior informal social control expectations	-0.361	-3.070	0.044	0.120	0.524 **	0.116	0.105
	-(1.09)	-(0.45)	(0.91)	(1.33)	(6.26)	(1.24)	(0.75)
Prior exercise of informal social control	0.013	10.198 *	0.014	0.146 **	0.083 *	0.571 **	-0.133 †
	(0.06)	(2.54)	(0.49)	(2.82)	(2.50)	(8.82)	-(1.77)
Prior violence	0.545 **	-1.566	0.002	0.029 †	-0.007	0.009	0.848 **
	(8.02)	-(1.14)	(0.17)	(1.78)	-(0.69)	(0.56)	(34.55)
Nearby prior violence	-0.100	2.190	-0.010	-0.028	0.000	0.034 †	0.017
	-(1.29)	(1.38)	-(0.88)	-(1.38)	-(0.03)	(1.79)	(0.64)
Intercept	0.459	-13.489 †	-0.096 †	0.214 *	0.135 †	-0.286 **	0.337 *
	(1.16)	-(1.67)	-(1.70)	(2.00)	(1.89)	-(2.82)	(2.35)
R-square	0.91	0.59	0.84	0.60	0.76	0.48	0.87

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. chi sq = 171.78 on 88 df, RMSEA = .082, CFI = .962*

Table 3. Results of cross-lagged simultaneous equations for drug crime

	Disadvantage		Residential instability		Ethnic heterogeneity		Neighborhood Social Ties		Informal Social Control Expectations		Exercise of Informal Social Control		Drug crime	
Prior disadvantage	0.770	**	0.697		0.007		0.001		-0.036	**	0.014		0.061	
	(18.84)		(0.81)		(1.13)		(0.10)		-(4.44)		(1.38)		(1.54)	
Prior residential instability	0.004		0.793	**	0.001	**	0.000		0.000		0.000		-0.010	**
	(1.25)		(11.40)		(3.06)		(0.38)		(0.67)		-(0.45)		-(2.98)	
Prior ethnic heterogeneity	0.010		-9.597		0.539	**	-0.007		-0.021		0.164	†	-0.563	†
	(0.03)		-(1.32)		(10.89)		-(0.08)		-(0.34)		(1.83)		-(1.70)	
Prior percent of residents aged 15 to 24 years	0.021		0.292		0.005	**	-0.014	**	-0.002		-0.002		-0.025	†
	(1.56)		(1.05)		(2.62)		-(3.73)		-(0.98)		-(0.61)		-(1.91)	
Nearby concentrated disadvantage	0.064	†	0.193		0.017	**	-0.007		-0.018	**	-0.030	**	-0.001	
	(1.71)		(0.25)		(3.13)		-(0.70)		-(2.72)		-(3.06)		-(0.03)	
Nearby residential instability	-0.012		0.273		-0.003	*	0.000		-0.003	†	0.006	**	0.003	
	-(1.35)		(1.47)		-(2.53)		-(0.18)		-(1.91)		(2.79)		(0.39)	
Nearby ethnic heterogeneity	-0.831		1.359		0.549	**	-0.247		-0.141		-0.010		0.782	
	-(1.50)		(0.12)		(6.93)		-(1.60)		-(1.43)		-(0.07)		(1.46)	
Nearby percent residents aged 15-24 years	-0.025	†	0.181		0.002		0.003		0.004		-0.001		0.016	
	-(1.68)		(0.57)		(0.94)		(0.60)		(1.42)		-(0.25)		(1.07)	
Prior neighborhood social ties	0.146		-8.181	†	-0.100	**	0.496	**	0.085	*	0.062		0.560	**
	(0.70)		-(1.87)		-(3.35)		(6.92)		(2.20)		(1.05)		(2.59)	
Prior informal social control expectations	-0.548	†	-0.624		0.041		0.108		0.540	**	0.137		-0.960	**
	-(1.69)		-(0.09)		(0.87)		(1.25)		(6.58)		(1.51)		-(2.71)	
Prior exercise of informal social control	-0.058		9.101	*	0.010		0.146	**	0.075	*	0.571	**	0.094	
	-(0.30)		(2.22)		(0.36)		(2.77)		(2.23)		(8.86)		(0.49)	
Prior drug crime	0.207	**	-0.111		0.006		0.007		0.000		-0.001		0.680	**
	(7.71)		-(0.20)		(1.60)		(1.17)		(0.09)		-(0.17)		(30.99)	
Nearby prior drug crime	-0.133	*	0.927		-0.014	†	-0.022		0.001		0.025	†	0.078	
	-(2.40)		(0.80)		-(1.71)		-(1.56)		(0.10)		(1.85)		(1.54)	
Intercept	0.509		-12.317		-0.093	†	0.226	*	0.124	†	-0.262	**	0.651	†
	(1.33)		-(1.54)		-(1.70)		(2.15)		(1.73)		-(2.66)		(1.77)	
R-square	0.91		0.58		0.85		0.62		0.77		0.49		0.82	

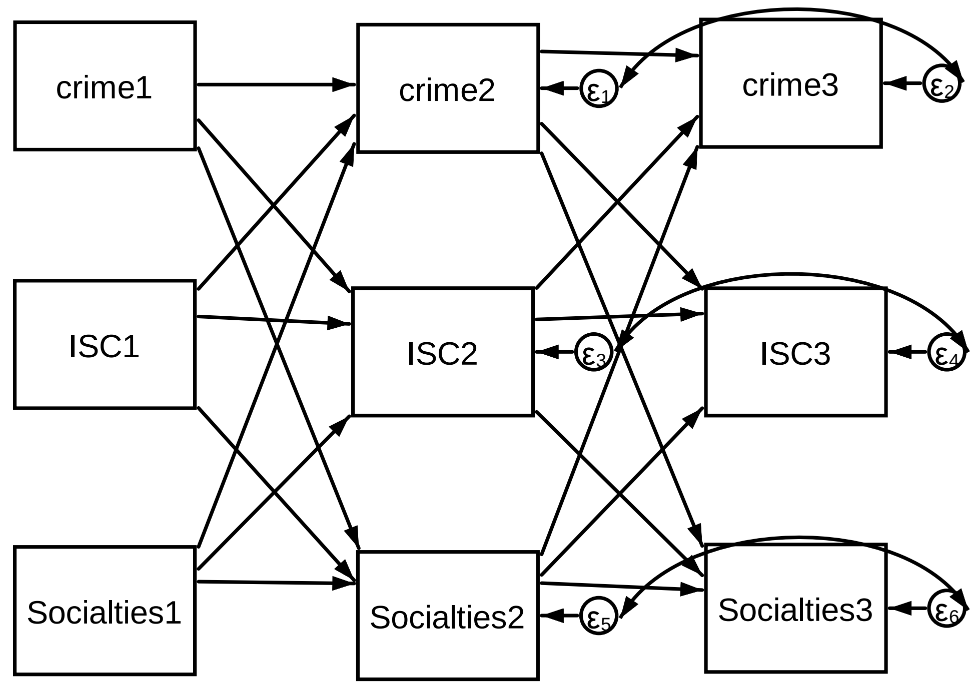
*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. chi sq = 193.29 on 88 df, RMSEA = .092, CFI = .953*

Table 4. Results of cross-lagged simultaneous equations for property crime

	Disadvantage		Residential instability		Ethnic heterogeneity		Neighborhood Social Ties		Informal Social Control Expectations		Exercise of Informal Social Control		Property crime	
Prior disadvantage	0.733	**	0.765		0.008		0.001		-0.033	**	0.013		0.304	**
	(17.73)		(0.89)		(1.27)		(0.09)		-(4.22)		(1.19)		(3.14)	
Prior residential instability	0.001		0.819	**	0.001	**	0.000		0.001		0.000		-0.042	**
	(0.32)		(11.94)		(2.98)		(0.37)		(0.89)		-(0.45)		-(5.23)	
Prior ethnic heterogeneity	-0.292		-10.222		0.532	**	-0.020		-0.035		0.162	†	-0.803	
	-(0.85)		-(1.44)		(10.83)		-(0.21)		-(0.59)		(1.80)		-(1.01)	
Prior percent of residents aged 15 to 24 years	0.002		0.267		0.005	**	-0.015	**	-0.002		-0.003		0.049	
	(0.12)		(0.96)		(2.61)		-(3.98)		-(1.01)		-(0.75)		(1.55)	
Nearby concentrated disadvantage	0.089	*	0.265		0.018	**	-0.007		-0.017	**	-0.030	**	0.148	†
	(2.39)		(0.34)		(3.27)		-(0.68)		-(2.61)		-(3.02)		(1.71)	
Nearby residential instability	-0.002		0.252		-0.003	*	0.000		-0.003	*	0.006	**	-0.020	
	-(0.25)		(1.36)		-(2.35)		-(0.07)		-(2.11)		(2.67)		-(0.96)	
Nearby ethnic heterogeneity	-0.586		1.143		0.544	**	-0.254	†	-0.110		0.005		0.205	
	-(1.09)		(0.10)		(7.02)		-(1.71)		-(1.16)		(0.03)		(0.16)	
Nearby percent residents aged 15-24 years	-0.032	*	0.205		0.003		0.004		0.004		-0.002		0.037	
	-(2.13)		(0.65)		(1.19)		(0.85)		(1.52)		-(0.52)		(1.03)	
Prior neighborhood social ties	-0.329		-7.569	†	-0.103	**	0.463	**	0.085	*	0.059		0.920	†
	-(1.53)		-(1.70)		-(3.31)		(6.57)		(2.20)		(0.99)		(1.66)	
Prior informal social control expectations	-0.206		-0.954		0.038		0.150	†	0.547	**	0.154	†	0.681	
	-(0.63)		-(0.14)		(0.80)		(1.80)		(6.89)		(1.69)		(0.76)	
Prior exercise of informal social control	0.142		10.203	*	0.017		0.148	**	0.077	*	0.552	**	-0.169	
	(0.73)		(2.52)		(0.61)		(2.92)		(2.34)		(8.69)		-(0.36)	
Prior property crime	0.075	**	0.029		0.001		0.005	**	-0.001		0.002		0.884	**
	(9.80)		(0.18)		(0.60)		(2.93)		-(0.62)		(0.90)		(51.00)	
Nearby prior property crime	-0.042		0.774		-0.003		-0.021	*	0.001		0.007		-0.135	
	-(1.17)		(1.04)		-(0.54)		-(2.13)		(0.09)		(0.72)		-(1.64)	
Intercept	0.441		-13.300	†	-0.110	*	0.219	*	0.128	†	-0.233	*	3.111	**
	(1.16)		-(1.69)		-(2.02)		(2.13)		(1.82)		-(2.34)		(3.49)	
R-square	0.92		0.59		0.84		0.62		0.77		0.48		0.91	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. chi sq = 224.56 on 88 df, RMSEA = .104, CFI = .945*

Figure 1. Conceptual model



Appendices

Appendix 1. Number of participants for waves 2, 3 and 4 of the ACCS

ACCS Wave	Average Population of ACCS Neighborhoods	Longitudinal Sample	Top-Up Sample	Total Sample Size	Average number of respondents per neighborhood
Wave 2	5,690	1,077	3,247	4,324	27.56 (Range: 12-54)
Wave 3	6,046	2,286	1,935	4,221	29.61 (Range: 13-67)
Wave 4	6,633	2,473	1,659	4,132	27.82 (Range: 10-47)

Appendix 2: Correlation Matrix Wave 4

	Expectations informal social control	Neighborhood social ties	Exercise informal social control	Concentrated disadvantage	Ethnic heterogeneity	Residential instability	Percent aged 15 to 24	Population density	Property crime	Violent crime	Drug crime
Expectations informal social control	1.00										
Neighborhood social ties	0.59	1.00									
Exercise informal social control	0.45	0.50	1.00								
Concentrated disadvantage	-0.68	-0.18	-0.14	1.00							
Ethnic heterogeneity	-0.42	-0.38	-0.15	0.31	1.00						
Residential instability	-0.21	-0.16	-0.04	0.11	0.16	1.00					
Percent aged 15 to 24	-0.41	-0.43	-0.26	0.26	0.45	0.27	1.00				
Population density	-0.37	-0.21	-0.21	0.24	0.45	0.28	0.52	1.00			
Property crime	-0.40	-0.08	-0.05	0.61	0.26	0.04	0.27	0.09	1.00		
Violent crime	-0.36	-0.06	0.01	0.64	0.22	0.01	0.22	0.05	0.90	1.00	
Drug crime	-0.28	-0.03	0.04	0.49	0.18	-0.07	0.18	0.04	0.69	0.82	1.00

Appendix 3. ABS Census and ACCS sample demographics

Demographics	Census 2006	Census 2011	ACCS Wave 2	ACCS Wave 3	ACCS Wave 4
Age (18 and over)	46.0 years	46.3 years	49.9 years	51.2 years	53.4 years
Gender (Male)	49.1%	49.3%	39.8%	40.8%	40.1%
Home Ownership (Own)	66.5%	65.3%	85.8%	86.8%	87.9%
Aboriginal and Torres Strait Islander	1.9%	2.3%	1.5%	0.9%	1.1%
Speaks English Only	85.3%	83.7%	93.3%	89.0%	93.8%
Born in Australia	73.4%	72.4%	75.5%	75.9%	75.6%
Employed (full time)	39.7%	39.0%	42.0%	38.5%	37.1%
University Education	11.7%	13.7%	31.2%	35.5%	33.9%
Different Address Five Years Ago	42.1%	37.6%	25.5%	23.3%	17.1%
Married	48.1%	47.3%*	63.8%	66.9%	66.6%
Median Household Income (Yearly)	$58953	$75414	$60,000 to $79,999	$60,000 to $79,999	$80,000 to $99,999
Religion					
Buddhism	1.7%	1.9%	1.7%	1.7%	0.6%
Christianity	64.7%	62.6%	63.2%	67.6%	70.5%
Hinduism	0.5%	0.9%	1.3%	1.4%	0.5%
Islam	0.6%	1.0%	1.6%	1.8%	0.6%
Judaism	0.1%	0.1%	0.8%	0.2%	0.1%
Other Religion	0.5%	0.8%	1.0%	0.9%	1.1%
No Religion	19.3%	22.9%	30.4%	26.3%	26.4%

Table A4. Results of nonrecursive simultaneous equations for violence

	Disadvantage		Residential instability		Ethnic heterogeneity		Neighborhood Social Ties		Informal Social Control Expectations		Exercise of Informal Social Control		Violence	
Prior disadvantage	0.717	**	0.678		0.009		0.003		-0.036	**	0.008		0.067	**
	(16.81)		(0.77)		(1.43)		(0.39)		-(5.25)		(0.56)		(3.33)	
Prior residential instability	0.003		0.793	**	0.001	**	0.000		0.000		0.000		-0.004	*
	(0.86)		(11.70)		(2.62)		(0.10)		(0.56)		-(0.33)		-(2.20)	
Prior ethnic heterogeneity	-0.083		-9.469		0.529	**	-0.018		-0.035		0.183	†	-0.150	
	-(0.24)		-(1.33)		(10.60)		-(0.20)		-(0.60)		(1.83)		-(0.90)	
Prior percent of residents aged 15 to 24 years	0.007		0.179		0.005	*	-0.014	**	-0.001		-0.003		0.004	
	(0.51)		(0.65)		(2.46)		-(3.98)		-(0.26)		-(0.83)		(0.64)	
Nearby concentrated disadvantage	0.066	†	0.257		0.017	**	-0.001		-0.015	*	-0.034	**	0.012	
	(1.73)		(0.33)		(3.21)		-(0.12)		-(2.27)		-(3.00)		(0.65)	
Nearby residential instability	-0.005		0.322	†	-0.003	*	0.000		-0.004	*	0.007	**	-0.006	
	-(0.61)		(1.74)		-(2.12)		-(0.15)		-(2.40)		(2.59)		-(1.45)	
Nearby ethnic heterogeneity	-0.516		2.267		0.569	**	-0.225		-0.091		0.017		-0.092	
	-(0.93)		(0.20)		(7.13)		-(1.59)		-(0.97)		(0.10)		-(0.35)	
Nearby percent residents aged 15-24 years	-0.032	*	0.184		0.002		0.002		0.003		-0.002		0.009	
	-(2.13)		(0.59)		(1.11)		(0.52)		(1.18)		-(0.43)		(1.22)	
Neighborhood social ties	-0.068		-9.476	*	-0.106	**	0.486	**	0.152	**	0.098		-0.041	
	-(0.32)		-(2.18)		-(3.50)		(9.14)		(3.27)		(0.98)		-(0.37)	
Informal social control expectations	-0.398		-2.951		0.049		0.190	†	0.488	**	0.056		0.153	
	-(1.20)		-(0.43)		(1.04)		(1.84)		(8.85)		(0.38)		(0.92)	
Exercise of informal social control	0.028		11.505	**	0.015		0.154	*	0.083	†	0.489	**	0.016	
	(0.15)		(2.89)		(0.53)		(2.09)		(1.65)		(8.56)		(0.16)	
Violent crime	0.592	**	-1.020		0.002		0.036	*	-0.016		0.007		0.781	**
	(9.41)		-(0.79)		(0.26)		(2.10)		-(1.53)		(0.34)		(28.07)	
Nearby violent crime	-0.113		2.193		-0.007		-0.030		0.003		0.032		0.026	
	-(1.48)		(1.41)		-(0.61)		-(1.48)		(0.39)		(1.39)		(0.77)	
Intercept	0.442		-13.217	†	-0.113	*	0.222	*	0.139	*	-0.260	*	0.353	†
	(1.14)		-(1.66)		-(2.02)		(2.23)		(2.15)		-(2.31)		(1.94)	
R-square	0.91		0.59		0.84		0.65		0.79		0.48		0.85	

*** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses. Nonrecursive equations using measure at previous time point as instrument to identify equation.*

Table A5. Results of nonrecursive simultaneous equations for property crime

	Disadvantage	Residential instability	Ethnic heterogeneity	Neighborhood Social Ties	Informal Social Control Expectations	Exercise of Informal Social Control	Property crime
Prior disadvantage	0.731 **	0.858	0.009	0.003	-0.034 **	0.012	0.400 **
	(17.73)	(1.00)	(1.45)	(0.53)	-(4.99)	(0.89)	(3.14)
Prior residential instability	0.000	0.790 **	0.001 **	0.000	0.000	0.000	-0.053 **
	-(0.09)	(11.67)	(2.69)	-(0.19)	(0.56)	-(0.51)	-(4.98)
Prior ethnic heterogeneity	-0.255	-9.452	0.537 **	-0.024	-0.041	0.173 †	-0.446
	-(0.74)	-(1.32)	(10.89)	-(0.27)	-(0.69)	(1.77)	-(0.41)
Prior percent of residents aged 15 to 24 years	0.002	0.233	0.005 **	-0.014 **	0.000	-0.003	0.064
	(0.18)	(0.83)	(2.70)	-(4.01)	-(0.17)	-(0.78)	(1.52)
Nearby concentrated disadvantage	0.087 *	0.251	0.017 **	-0.001	-0.015 *	-0.032 **	0.138
	(2.35)	(0.32)	(3.16)	-(0.07)	-(2.35)	-(2.89)	(1.16)
Nearby residential instability	-0.002	0.292	-0.003 *	0.000	-0.004 *	0.007 *	0.000
	-(0.26)	(1.57)	-(2.17)	-(0.14)	-(2.35)	(2.54)	(0.01)
Nearby ethnic heterogeneity	-0.623	2.242	0.547 **	-0.228 †	-0.065	0.048	0.136
	-(1.15)	(0.20)	(7.06)	-(1.67)	-(0.71)	(0.30)	(0.08)
Nearby percent residents aged 15-24 years	-0.033 *	0.147	0.003	0.002	0.003	-0.003	0.011
	-(2.21)	(0.47)	(1.19)	(0.60)	(1.23)	-(0.76)	(0.23)
Neighborhood social ties	-0.302	-8.580 †	-0.101 **	0.481 **	0.162 **	0.094	0.031
	-(1.43)	-(1.95)	-(3.33)	(9.33)	(3.64)	(0.95)	(0.05)
Informal social control expectations	-0.242	-0.628	0.042	0.189 *	0.506 **	0.130	1.840 †
	-(0.74)	-(0.09)	(0.90)	(2.05)	(9.24)	(0.91)	(1.77)
Exercise of informal social control	0.117	10.985 **	0.015	0.152 *	0.060	0.474 **	-0.314
	(0.61)	(2.74)	(0.52)	(2.09)	(1.20)	(8.63)	-(0.50)
Property crime	0.069 **	-0.056	0.000	0.004 *	-0.002 †	0.002	0.825 **
	(9.70)	-(0.38)	(0.07)	(2.23)	-(1.77)	(0.83)	(40.16)
Nearby property crime	-0.053	0.726	-0.003	-0.022 *	0.003	0.008	-0.231 *
	-(1.47)	(0.98)	-(0.53)	-(2.41)	(0.53)	(0.71)	-(2.12)
Intercept	0.547	-12.373	-0.115 *	0.248 **	0.128 *	-0.236 *	3.231 **
	(1.46)	-(1.58)	-(2.13)	(2.60)	(1.97)	-(2.16)	(2.80)
R-square	0.91	0.58	0.84	0.67	0.80	0.50	0.89

*** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses. Nonrecursive equations using measure at previous time point as instrument to identify equation.*

Table A6. Results of nonrecursive simultaneous equations for drug crime

	Disadvantage	Residential instability	Ethnic heterogeneity	Neighborhood Social Ties	Informal Social Control Expectations	Exercise of Informal Social Control	Drug crime
Prior disadvantage	0.759 **	0.855	0.008	0.005	-0.037 **	0.014	0.101 *
	(18.72)	(1.00)	(1.42)	(0.65)	-(5.49)	(1.04)	(2.06)
Prior residential instability	0.005	0.781 **	0.001 **	0.000	0.000	0.000	-0.011 **
	(1.54)	(11.28)	(2.89)	(0.09)	(0.57)	-(0.38)	-(2.74)
Prior ethnic heterogeneity	0.050	-9.885	0.535 **	-0.026	-0.028	0.177 †	-0.774 †
	(0.14)	-(1.36)	(10.83)	-(0.28)	-(0.48)	(1.78)	-(1.88)
Prior percent of residents aged 15 to 24 years	0.021	0.222	0.005 **	-0.013 **	-0.001	-0.002	-0.019
	(1.56)	(0.80)	(2.60)	-(3.80)	-(0.23)	-(0.56)	-(1.19)
Nearby concentrated disadvantage	0.062 †	0.299	0.017 **	-0.001	-0.017 *	-0.033 **	0.021
	(1.66)	(0.38)	(3.14)	-(0.08)	-(2.53)	-(2.95)	(0.46)
Nearby residential instability	-0.013	0.302	-0.003 *	-0.001	-0.003 *	0.006 *	0.006
	-(1.50)	(1.63)	-(2.31)	-(0.37)	-(2.14)	(2.50)	(0.58)
Nearby ethnic heterogeneity	-0.880	3.006	0.558 **	-0.215	-0.094	0.032	1.053
	-(1.59)	(0.26)	(7.05)	-(1.49)	-(0.99)	(0.20)	(1.60)
Nearby percent residents aged 15-24 years	-0.029 †	0.179	0.002	0.002	0.003	-0.003	0.013
	-(1.96)	(0.57)	(1.05)	(0.49)	(1.28)	-(0.57)	(0.72)
Neighborhood social ties	0.099	-9.129 *	-0.101 **	0.504 **	0.167 **	0.097	0.290
	(0.48)	-(2.11)	-(3.45)	(9.69)	(3.79)	(1.02)	(1.08)
Informal social control expectations	-0.588 †	-0.095	0.048	0.157	0.505 **	0.122	-0.465
	-(1.82)	-(0.01)	(1.04)	(1.63)	(9.12)	(0.86)	-(1.13)
Exercise of informal social control	-0.066	10.923 **	0.013	0.161 *	0.056	0.472 **	0.333
	-(0.34)	(2.68)	(0.47)	(2.20)	(1.12)	(8.46)	(1.34)
Drug crime	0.229 **	-0.282	0.004	0.007	-0.001	0.002	0.629 **
	(9.87)	-(0.58)	(1.26)	(1.01)	-(0.21)	(0.24)	(30.24)
Nearby drug crime	-0.155 **	1.101	-0.011	-0.023	0.005	0.023	0.114 †
	-(2.85)	(0.96)	-(1.37)	-(1.60)	(0.65)	(1.42)	(1.91)
Intercept	0.588	-12.332	-0.106 *	0.250 *	0.107 †	-0.251 *	0.524
	(1.56)	-(1.55)	-(1.97)	(2.55)	(1.65)	-(2.31)	(1.18)
R-square	0.91	0.58	0.85	0.66	0.80	0.50	0.81

*** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses. Nonrecursive equations using measure at previous time point as instrument to identify equation.*