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Violence in urban neighborhoods:

A longitudinal study of collective efficacy and violent crime

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Biography

John R. Hipp is a Professor in the departments 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, American Journal of Public Health, Social Forces*, *Social Problems, Social Networks, Journal of Research in Crime and Delinquency, Journal of Quantitative Criminology, Mobilization, Health & Place*, *City & Community*, *Crime & Delinquency*, *Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology*, *Psychological Methods*, and *Structural Equation Modeling*.

Rebecca Wickes is a Senior Lecturer in Criminology in the School of Social Science at the University of Queensland in Brisbane, Australia. Dr. Wickes is the lead investigator of the Australian Community Capacity Study, a multisite, longitudinal study of place. Her research focusses on demographic changes in urban communities and their influence on community regulation, crime and disorder. She has published in journals such as *Criminology*, *Journal of Research in Crime and Delinquency*, *American Journal of Community Psychology*, *the Journal of Urban Affairs*, among others.

Abstract:

Objectives: Cross-sectional studies consistently find that neighborhoods with higher levels of collective efficacy experience fewer social problems. Particularly robust is the relationship between collective efficacy and violent crime, which holds regardless of the socio-structural conditions of neighborhoods. Yet due to the limited availability of neighborhood panel data, the temporal relationship between neighborhood structure, collective efficacy and crime is less well understood.

Methods: In this paper, we provide an empirical test of the collective efficacy-crime association over time by bringing together multiple waves of survey and census data and counts of violent crime incident data collected across 148 neighborhoods in Brisbane, Australia. Utilizing three different longitudinal models that make different assumptions about the temporal nature of these relationships, we examine the reciprocal relationships between neighborhood features and collective efficacy with violent crime. We also consider the spatial embeddedness of these neighborhood characteristics and their association with collective efficacy and the concentration of violence longitudinally.

Results: Notably, our findings reveal no direct relationship between collective efficacy and violent crime over time. However, we find a strong reciprocal relationship between collective efficacy and disadvantage and between disadvantage and violence, indicating an indirect relationship between collective efficacy and violence.

Conclusions: The null direct effects for collective efficacy on crime in a longitudinal design suggest that this relationship may not be as straightforward as presumed in the literature. More longitudinal research is needed to understand the dynamics of disadvantage, collective efficacy, and violence in neighborhoods.

Key words: Collective Efficacy, Violence, Disadvantage, Neighborhood

INTRODUCTION

The spatial concentration of crime is strongly associated with disadvantage and the ecological structure of urban neighborhoods. For much of the last century, scholars have explained the concentration of crime and disorder through a social disorganization lens. From this perspective, serious crime flourishes when the neighborhood networks necessary for maintaining informal social control have broken down (Bursik & Grasmick, 1993; Hunter, 1985; Kornhauser, 1978; Sampson & Groves, 1989; Shaw & McKay, 1942; Skogan, 1986). Contemporary reformulations of social disorganization theory suggest that a neighborhood's shared expectations for action are also central to the regulation of crime and disorder (Sampson, Raudenbush and Earls, 1997). While networks generate a capacity for informal social control, collective efficacy or the collective-action orientation of a neighborhood is the most proximate mechanism associated with lower crime (Morenoff, Sampson and Raudenbush 2001, Sampson, 2006; Sampson, 2012; Sampson et al., 1997).

Many cross-sectional studies in both developed and developing countries find that neighborhoods with low collective efficacy experience higher levels of social problems, particularly crime (see for example, Browning, Leventhal, and Brooks-Gunn, 2005; Franzini Caughy, Spears and Esquer, 2005; Maimon, Browning, and Brooks-Gunn, 2010; Mazerolle, Wickes and McBroom, 2010; Morenoff et al., 2001; Sampson et al., 1997; Sampson and Wikstrom, 2008; Zhang, Messner, and Liu, 2007). From this literature, we know that poverty, ethnic/racial concentration and residential mobility are negatively associated with collective efficacy (Sampson et al., 1997) and that a neighborhood's collective efficacy is influenced by the socio-structural composition of surrounding neighborhoods (Sampson, 2012; Sampson et al., 1999). Sampson (2012) also suggests that neighborhood structures, collective efficacy and violence may influence each other over time (Sampson, 2012). Yet there are significant gaps in our knowledge of collective efficacy. For example, few studies examine what generates and sustains collective efficacy over time (Wickes, Hipp, Sargeant and Homel, 2013). Even fewer consider the temporal dynamics that might be associated with the collective efficacy-crime association.

Due to the limited availability of neighborhood panel data[1], our understanding of the spatial and temporal nature of collective efficacy and crime link is incomplete. In fact, there is little theoretical guidance about the time period over which these causal relationships should occur. In this paper we draw on the pioneering work of Sampson and his colleagues and extend the literature in three important ways. First, using measures that are nearly identical to those from the Project for Human Development in Chicago Neighborhoods (PHDCN) survey, we bring together three waves of neighborhood survey and census data and provide the first multi-wave study of the relationship between the structural characteristics of an area and collective efficacy across 148 neighborhoods in Brisbane, Australia. Second, we estimate three different longitudinal models that each make different assumptions about the temporal period in which these reciprocal relationships take place between neighborhood characteristics and collective efficacy with violent crime. Third, we consider the spatial embeddedness of these neighborhood features over time and their association with collective efficacy and the concentration of violence.

In what follows we discuss the intellectual roots of collective efficacy theory. We then discuss the key findings emerging from the collective efficacy literature with a specific focus on

[1] At the time of writing, only the Project for Human Development in Chicago Neighborhoods (PHDCN) and LA FANS in Los Angeles have collected more than one wave of neighborhood survey data that specifically captures collective efficacy (Sampson, 2012).

the spatial interdependency of the neighborhood composition, collective efficacy and violence and the stability of social processes like collective efficacy over time. We consider different possibilities regarding the temporal period over which these processes might operate. This is followed by an overview of our key data source, the Australian Community Capacity Study (ACCS), and our analytic approach. Our findings demonstrate the strong reciprocal relationship between collective efficacy and disadvantage and between disadvantage and violence. They also show that the changing context of neighboring areas must also be considered in understanding violence in the focal neighborhood.

LITERATURE REVIEW

The study of neighborhood effects in criminology commenced in earnest with Shaw and McKay's (1942) citywide study of delinquency. They identified that particular zones not only had the highest rate of delinquents, they were areas characterized by significant residential mobility, disadvantage and ethnic and racial concentration (Shaw and McKay, 1942). Shaw and McKay (1942) argued that although criminal activity was related partly to the individual's propensity to commit a crime, it was the constant exposure to contradictory standards of behavior, combined with the breakdown of community norms and conventional values that explained the spatial concentration of crime in the zones closest to the city center. The main finding of Shaw and McKay's (1942) research was that despite complete population turnover, high crime neighborhoods remained crime prone decades into the future.

In the social disorganization literature a "web of social relationships" was considered necessary for regulating crime (Kornhauser, 1978:45; see also Bursik, 1988; Bursik and Grasmick, 1993; Hunter, 1985). These social ties were deemed particularly important for fostering informal social control that can reduce neighborhood crime, however, more recently scholars have questioned the regulatory capacity of neighborhood social ties. While social ties may be instrumental for informal social control (Bursik, 1999; Sampson, 1988; Sampson and Groves, 1989), studies find that neighborhood ties have limited direct effects on crime (Warner and Roundtree, 1997) and can impede residents' ability to engage in the informal social control of crime and disorder (Pattillo, 1998). Sampson and Groves' (1989) research revealed that the more important mechanism for controlling crime was the community's capacity to enforce informal social control norms. They found that the ability of the community to exercise control over adolescent peer groups was the more proximate intervening process associated with lower crime (Sampson and Groves, 1989). Marking what is referred to as the "process turn" in the study of neighborhood effects (Sampson, 2012:47), Sampson and his colleagues emphasized the importance of collective efficacy, or the "collective capacity for social action" over neighborhood ties for effective crime control (Sampson, 2002; Sampson, 2012; Sampson et al., 1997, Sampson et al., 1999; Morenoff et al., 2001).

Originating from Albert Bandura's (1995, 1997, 2001) social cognitive theory, collective efficacy is formally defined as "a group's shared belief in its conjoint capabilities to organize and execute the courses of action required to produce given levels of attainments" (Bandura, 1997: 477) and is separate from the sum of individual attributes. Thus collective efficacy represents the emergent property of a group that is central to group level performance. Sampson views collective efficacy as a concept applicable not only to small groups, but one that is relevant to understanding the differential capacities of neighborhoods to prevent crime and disorder. Using data resulting from the Project of Human Development in Chicago Neighborhoods (PHDCN)[2],

[2] The PHDCN is a longitudinal project sponsored by the MacArthur Foundation in partnership with the National Institutes of Justice and Mental Health, Harvard School of Public Health, the Administration on Children, Youth and Families of the U.S. Department of Health and Human Services and the U.S. Department of Education. It is a multi-

Sampson and his colleagues (Sampson et al., 1997) examined the perceived capacity of fellow residents to engage in informal social control and the level of social cohesion and trust within the neighborhood, and the relationship with neighborhood violence.

Since the publication of the 1997 *Science* article, the link between collective efficacy and a range of social problems is evidenced in many studies, almost all of which have cross-sectional designs. Residents of communities with high levels of collective efficacy report higher levels of self-rated health (Browning and Cagney, 2002; Franzini et al., 2005) and demonstrate greater parental monitoring (Rankin and Quane, 2002). Moreover, the presence of collective efficacy appears to mediate low parental monitoring as it relates to the timing of first intercourse for girls and boys (Browning et al., 2005) and is associated with a higher likelihood that women will formally or informally report instances of domestic violence (Browning, 2002). Studies in Australia (Mazerolle et al., 2010), the U.K. (Wikstrom et al., 2012), and Sweden (Sampson and Wikstrom, 2008) also support the association between collective efficacy and violence and disorder. Not surprisingly, scholars and policy makers alike are interested in understanding the antecedents of collective efficacy, the threats to collective efficacy and its relationship with social problems over time and space.

Poverty, Collective Efficacy and Violence: Their Spatial and Temporal Dynamics

Collective efficacy is strongly influenced by the socio-demographic composition of the focal neighborhood. Concentrated disadvantage, residential instability and immigrant concentration correspond with lower levels of collective efficacy at the neighborhood level in cross-sectional studies. Taken together, these variables account for 70% of the variability in collective efficacy across the 343 neighborhoods in Chicago (Sampson et al., 1997). Of these

million dollar project examining the social, criminological, economic, organizational, political and cultural structures of Chicago's communities.

structural characteristics, concentrated disadvantage appears the most deleterious for collective efficacy. Scholars have argued that poverty significantly reduces the informal social control capacity of the neighborhood (Bursik and Grasmick, 1993; Morenoff et al., 2001) and as a consequence increases one's exposure to violence and victimization (Bingenheimer et al., 2005; Morenoff et al., 2001; Sampson et al., 1997). In their study of Chicago neighborhoods, Morenoff and his colleagues (2001) find that a one standard deviation increase in disadvantage was associated with a 40% higher homicide rate. Sampson (2006) argues that poverty sets in motion a cycle that undermines collective efficacy, which in turn sets in play a range of problems that deepens and reinforces poverty.

The association between poverty, collective efficacy and violence holds across cities in the U.S. and internationally. In a cross-sectional study of Australian neighborhoods, Mazerolle and colleagues (2010) find that concentrated disadvantage and residential mobility influence collective efficacy in much the same way as they do in Chicago and that collective efficacy appeared to mediate the direct effect of these structural characteristics on violence. Later studies in Australia suggest that disadvantage, the percentage of residents speaking a language other than English and population density also negatively influence collective efficacy for task specific problems like the control of children, violence and more civic related problems (Wickes et al., 2013).

Although neighborhood socio-demographic characteristics, such as poverty, demonstrate significant durability, neighborhood change does occur (Sampson, 2012). Yet for the most part, this change is predominantly in the direction of more deeply entrenched poverty and violence (Sampson, 2012; Taylor and Covington, 1988; Wilson 1987). As Sampson and Raudenbush (2006: 177) suggest "despite the vulnerabilities or assets associated with a neighborhood's internal characteristics, its rate of poverty change is directly linked to changes in the surrounding network of neighborhood poverty". Theoretically then the relationship between neighborhood characteristics, collective efficacy and crime is likely to be temporal and reciprocal.

While we know that increasing poverty leads to an increase in a range of social problems, including violence, we do not fully understand the reciprocal relationship between disadvantage, collective efficacy and violence over time. Due to the limited availability of panel data, there are no studies that examine the reciprocal relationship between neighborhood structure, collective efficacy and violence across more than two time points (Sampson, 2012). Thus it is unclear whether collective efficacy is a protective factor that prevents future violence or if violence undermines the development of collective efficacy, which may then lead to greater levels of violence. Social disorganization perspectives would argue for the former: structural characteristics of the neighborhood break down the regulatory mechanisms, like collective efficacy, which in turn leads to higher crime (Sampson et al., 1999). There is some support for this position. Several studies find that economic disadvantage, racial composition and residential instability significantly predict violence, in particular homicide (Hipp, 2010; Kubrin and Herting, 2003; Land, McCall and Cohen, 1990; Sampson et al., 1997). In their longitudinal examination of homicide in St. Louis, Kubrin and Herting (2003) found that disadvantage and residential mobility was associated with both the initial levels and trends of different types of homicide.

Yet others argue that crime is actually the catalyst for neighborhood change. Skogan's (1990) disorder and decline model posits that crime has a direct influence on residents' behavior (residents leave the area) and perceptions (residents feel less safe and retreat from social life). As Boggess and Hipp (2010) argue, crime encourages dissatisfaction with the neighborhood which in turn promotes an exodus of those residents with the means to relocate. That crime itself may play a role in how neighborhoods change (Bursik, 1988; Felson 2002; Miethe and Meier 1994; Skogan 1990) suggests the possibility of a reciprocal relationship between crime, the socio-structural characteristics of the neighborhood and the neighborhood processes necessary for regulating unwanted behavior. Thus violence might lead to greater instability and increase disadvantage, which will in turn diminish collective efficacy, leading to even more crime. Indeed, a longitudinal study of neighborhoods across 13 cities found that neighborhoods with higher levels of violent crime at the initial time point experienced larger increases in concentrated disadvantage over the subsequent decade, and that this effect was particularly pronounced for neighborhoods with very high levels of violence (Hipp, 2010).

The degree to which neighborhoods can successfully prevent violence is not only determined by the ecological structure of the focal neighborhood, but is potentially dependent upon nearby neighbors (Morenoff et al., 2001). Spatial dynamics are arguably important in explaining the dynamic relationship between concentrated disadvantage, collective efficacy and violence and evidence suggests that disadvantaged neighborhoods with high levels of violence tend to co-exist in space (Morenoff et al., 2001; Mears and Bhati, 2006; Sampson, 2012; Tita and Greenbaum, 2009).

Poverty and crime are strongly related to each other and exhibit significant spatial clustering (Peterson and Krivo, 2010). This is perhaps unsurprising given the strong relationship between poverty and violence more generally, yet even after controlling for other community conditions, including previous violence, disadvantage in the focal and neighboring areas can lead to higher violence. In their study of the spatial relationship between 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 neighboring communities. This leads them to 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, Kubrin and Hipp (2014) find that concentrated disadvantage in the area surrounding a block group has a positive relationship with crime in blocks.

It is possible that neighborhood collective efficacy may also be influenced by ecological conditions of neighboring areas. In the U.S., collectively efficacious neighborhoods 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 et al., 2001; Sampson, 2012; Sampson et al., 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. Thus "concentrated disadvantage, crime and collective efficacy are spatially interrelated in ways that go beyond chance expectations" (Sampson, 2012:240).

Temporal Periods and Causal Order

For each of the relationships of import to collective efficacy theory, there is little theoretical guidance regarding the time period in which they should play out. Taylor (2015) discusses at length the importance of considering the proper causal time length when specifying statistical models—failing to do so can result in improper specifications. Given this theoretical uncertainty, we exploit the longitudinal nature of our data (in which each wave of the survey data were collected 2-3 years apart) to empirically test three possible time periods in which these processes might operate (rather than assuming any one in particular).

One perspective argues that the relationship between collective efficacy and violence in neighborhoods plays out in a much shorter time period than two years: thus, an increase in collective efficacy would be expected to result in reduced violence in a manner of weeks or months, not two years. And likewise, increases in violence would have a relatively quick and negative effect on perceived collective efficacy (again, in a matter of weeks or months, not two years). Such a model effectively requires a simultaneous equations model given that our data are coarser-grained temporally. Our longitudinal data is nonetheless useful in that it provides plausible instrumental variables for such a model (MacDonald, Hipp, and Gill 2013; Paxton, Hipp, and Marquart-Pyatt 2011). This model is shown in Figure 1a, in which time 1 violence serves as an instrumental variable for the effect of time 2 violence on time 2 collective efficacy. This is because we would expect that violence at one time point will be strongly dependent on the level of violence at the prior time point, but collective efficacy at the present time point would be dependent on current levels of violence but not levels of violence at prior time points. And likewise, time 1 collective efficacy serves as an instrumental variable for the effect of time 2 collective efficacy on time 2 violence. In this case, a neighborhood with high levels of collective efficacy at one time point is likely to remain a high collective efficacy neighborhood, suggesting a strong positive relationship, but whereas the level of violence will be dependent on current levels of collective efficacy in this model, there is no reason to expect it to be impacted by prior levels of collective efficacy.

<<<Figure 1a, 1b, and 1c about here<<<

A second perspective argues that the causal process actually takes longer than weeks or months. Thus, it takes a period of time after which collective efficacy has increased to result in action that makes offenders aware that this location is not a suitable target given the likely response through informal social control. Likewise, residents are not necessarily immediately aware that crime events are increasing, but instead it takes a period of time to become aware of this change (Hipp, Tita, and Greenbaum 2009). As residents become aware of this change, levels of collective efficacy would go down. This perspective suggests that this time period may be in the range of two years, which implies that a two-year cross-lagged model may be appropriate. This model is shown in Figure 1b (Berry 1984).

A third perspective argues that the process takes even longer than two years. When we consider the effect of crime on neighborhood characteristics such as residential instability, racial composition, or income composition, it may be that levels of crime need to rise for a period of time even longer than a year or two to induce mobility. Likewise, it may take longer for residents to change their assessment of collective efficacy. And it may take higher levels of collective efficacy even longer to actually reduce neighborhood violence. This perspective suggests that a 2-year lag is too short, and that a longer period is required to model these processes. We model this by excluding our middle wave of data, and modeling a 5-year cross lagged model between waves 1 and 3 of our data as shown in Figure 1c.

The Present Research

In this paper we bring together three waves of panel data survey data (collected in 2007, 2010 and 2012) and two waves of census data (collected in 2006 and 2011) to examine spatial and temporal relationship between the socio-structural composition of the neighborhood, collective efficacy and rates of violence across 148 neighborhoods in Brisbane, Australia. The time frame of this longitudinal study provides a unique context in which to examine the reciprocal relationships of interest to this study. In the last decade Brisbane has experienced significant population growth due to increases in both immigration and internal migration (ABS, 2012; Hugo, Feist and Tan, 2013), resulting in increased diversity. In 2001, 9.2% of Brisbane's residents spoke a language other than English at home, in 2011, this figure reached 13.2%. While historically the bulk of Brisbane's immigrant population has come from the United Kingdom and New Zealand, recent trends have seen substantial growth in Asian immigration, particularly in the Indian and Chinese population (ABS, 2012). Affiliations with non-Christian religions like Hinduism and Islam have also been on the rise (ABS, 2012). According to social disorganization theory and its more contemporary reformulation, collective efficacy theory, changes in these socio-demographic characteristics can negatively impact social cohesion and generate confusion around norms of informal social control (Sampson et al., 1997).

METHODS

The Research Site

Located in South East Queensland, the longitudinal component of the ACCS focuses on the Greater Brisbane area. Brisbane, the state capital of Queensland, is Australia's third largest city with an estimated population of over 2 million people covering 15825.9 square kilometers. The five biggest industries in Brisbane are health care, retail, manufacturing, professional scientific and technical services and education. The Brisbane region provides an optimal research site to test the core tenets of collective efficacy theory. Brisbane has experienced considerable growth in recent years with the population increasing by 23% between 2001 and 2011. Brisbane also has one of the largest metropolitan Indigenous populations in Australia. In recent years, the immigrant population of Queensland broadly, and Brisbane specifically, has steadily increased and diversified boasting residents from over 300 different countries speaking nearly 30 languages. Brisbane has also become home to many immigrants from war torn countries (ABS, 2012).

Longitudinal Sample Design

We focus on waves 2, 3 and 4 of the Brisbane ACCS sample given that wave 1 used neighborhood units of analysis that are not comparable to those in the later waves. The survey comprises 148 randomly drawn neighborhoods[3] from a possible 429 neighborhoods in the Brisbane Division. The average population of the ACCS neighborhoods is about 6,000 (Appendix 1) (for further information on the ACCS study design please see http://www.uq.edu.au/accs). The ACCS neighborhoods are somewhat larger than census tracts in the U.S., where the average size of the census tract is approximately 4,000 inhabitants with a minimum of around 1,200 and a maximum of 8,000 residents. Yet we note that research examining the effects of neighborhood collective efficacy on perceptions of violence and rates of violence have relied on much larger units of analysis. Sampson and his colleagues employed neighborhood clusters with an average size of 8,000 residents (Sampson, 2012; Sampson et al., 1997). In later analyses of the PHDCN data, these neighborhood clusters were aggregated up to territorial communities with an average of 11,000 respondents. The ecometric properties for these larger territorial communities were "virtually equivalent" to the neighborhood clusters (Sampson, 2012: 443).

Survey Process and Participant Sample

The ACCS surveys were conducted by the Institute for Social Science Research at the University of Queensland. Trained interviewers utilized computer-assisted telephone interviewing to administer the survey. The in-scope survey population comprised all people aged 18 years or over who were usually resident in private dwellings with telephones in the selected

[3] 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.

neighborhoods in Brisbane[4]. Particular focus was placed on contacting those who had participated in previous waves. All participants were randomly selected. Response rates over the three waves ranged from 36% to 43%, and cooperation rates ranged from 46% to 62%[5]. Appendix 2 shows that the sample is similar to the Census measures of these neighborhoods for several measures; however, the sample does over-represent females, home owners, English only speakers, older, married, highly educated, and those who have not moved recently. We therefore account for these compositional effects in our collective efficacy measure as described shortly, an approach that is preferable to using survey weights (Winship and Radbill 1994). Information on the final sample composition is provided in Appendix 1.

<Table 1 here>

Additional Data Sources

Australian Bureau of Statistics (ABS) census data from 2006 and 2011 were merged with the ACCS longitudinal study. Census data include a range of variables empirically derived from the neighborhood effects literature (Bursik, 1988; McMillan and Chavis, 1986; Sampson et al., 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.

[4] 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, 2011). By comparison, in the US there were over 45% mobile only users in 2014 (Blumberg and Luke, 2015).

[5] 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. This is true for the ACCS surveys response rate. Yet the response rates for ACCS are on par with or indeed higher than other studies in Australia and the United States using phone contact (Duncan and Mummery, 2007; Pickett, Chiricos, Golden and Gertz, 2012; Lai, Zhao and Longmire, 2012; Larsen et al., 2004; Wood, Giles-Corti and Bulsara, 2012).

The Queensland Police Service (QPS) provided crime incident information aggregated to the suburb level for the Brisbane area. The Queensland Police Service (QPS) crime incident data represents monthly counts of reported offences in all suburbs in South-East Queensland from 2005 to 2013. In this paper we used crime incident data for violent crime which includes homicide, other homicide (e.g. manslaughter), assaults and robbery.

Measures

Dependent variable

Our key outcome measure is violent crime in the neighborhood. This measure is based on official crime reports to the police, and is the *violent crime rate* per 1,000 persons. To smooth out yearly fluctuations in crime, the violent crime rate is averaged over the two years nearest each survey wave. The violent crime count includes homicide, attempted murder, other homicide, conspiracy to murder, manslaughter (excluding by driving), driving causing death, grievous assault, assaults (excluding sexual), serious assault, serious assault (other), common assault, armed robbery and robbery. Although official crime reports suffer from under-reporting, a concern would be systematic under-reporting in certain neighborhoods; however, Baumer (2002) tested and found no relationship between the rate of reporting such serious violent events and key structural measures of neighborhoods, including economic disadvantage.

Independent variables

Our primary variable of interest is collective efficacy. We constructed a measure of *collective efficacy* based on survey responses. This measure contains items that are identical to those used in the PHDCN in the original study of collective efficacy (Sampson et al., 1997). These items are reliable at both the individual ($\alpha = 0.75$) and neighborhood level ($\alpha = 0.93$). Approximately 18%

of the variation in this measure is between neighborhoods. Our measure of collective efficacy was adjusted for compositional effects. We correct 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. This measure was constructed based on factor scores from a maximum likelihood factor analysis, and then standardized factor scores were constructed with mean of 0 and standard deviations of 1[6]. We estimated fixed effects models in which the outcome measures were the previously computed factor score, and included indicator variables for all neighborhoods, as well as several individual characteristics that might systematically impact our measure of collective efficacy.[7] We then used the estimated coefficients for each of the neighborhoods from this analysis as estimates of the amount of collective efficacy in the neighborhood in the models once accounting for these household characteristics.

Drawing on the social disorganization and collective action literatures, we included several neighborhood level control variables based on census data from the Australian Bureau of Statistics (ABS) from 2006 and 2011. We constructed a measure of *residential instability* as the percentage new households in the last five years. *Concentrated disadvantage* was constructed as a factor score combining three measures: median household income; unemployment rate; percent

[6] Factor analysis provides specific weights to each of the variables that compose the measure, which are analogous to an item response theory (IRT) approach; see Kamata and Bauer (2008) for the analytical proof that these approaches are identical.

[7] This equation is: $y_{ij} = \alpha + N_j\Gamma_N + X_{ij}\Gamma_X + \varepsilon_{ij}$; where y_{ij} is the factor score of collective efficacy as reported by the i-th respondent of I respondents in the j-th neighborhood, α is an intercept, N_j is an indicator of the neighborhood in which the respondent lives, Γ_N is a vector of the effects of these neighborhoods on collective efficacy, X is a matrix of the exogenous household-level predictors, Γ_X is a vector of the effects of these predictors on the subjective assessment, and ε_{ij} is a disturbance term. The following individual level characteristics are included in the model: 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).

one parent households.[8] A measure of *language heterogeneity* was constructed as a Herfindahl index based on nine language groups.[9] To capture those in the prime offender age group, we constructed a measure of the *percent aged 15 to 24*. Table 1 presents the summary statistics for the variables used in the analyses at each wave. To demonstrate the amount of variability in these measures over the study period, the last two columns show: 1) the standard deviation of a measure of the difference between wave 1 and wave 3 for each neighborhood for the variable of interest; 2) the ratio of this standard deviation of change over the time period to the standard deviation of the measure at a single time point (wave 3). There is a fair amount of change even over this limited period of time, as the amount of variability is about ½ that across neighborhoods at a single point in time.

<<<Table 1 about here>>>

Analytic Approach

As mentioned earlier, we estimated three different models that each make different assumptions about the temporal period in which these processes operate. All of the models account for possible feedback effects. Two of our models were estimated as cross-lagged simultaneous equation models (Berry 1984). This approach allows us to take into account the possibility of autocorrelated error structures over time (by allowing correlations between the error terms for each outcome variable in adjacent time periods), correlated errors among measures at the same time point (by allowing correlations between the error terms for each outcome variable at the same time point) and changing levels of the outcome variables over time

[8] Note that using factor scores for some of our measures that are standardized to a mean value of 0 at each time point is not problematic given that we are not estimating latent trajectory models attempting to capture change over time. Instead, our models are interested in marginal change in the outcome variable at a point in time given a marginal change in the covariate. Thus, the centering of the variables does not impact the substantive interpretation of our results, and is captured in the intercept terms estimated at each time point.

[9] 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.

(by estimating a unique intercept value at each time point). For each outcome variable, we can write the equation as:

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

where y_{1t} is, for example, 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 (including violent crime, in this case) 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 violent victimization 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. Given that we have three waves (t=1-3) for the collective efficacy and crime data, the equations for collective efficacy and violence appear two times (as they cannot be estimated for the first wave as there are no t-1 observations at that point) in our 2-year lag model (Figure 1b).[10] In the other cross-lagged models—using just waves 1 and 3 as shown in Figure 1c—the equations for collective efficacy and violence appear just once. The three census outcome variables (concentrated disadvantage, residential instability, and language heterogeneity) have one equation each in both models which regresses the 2011 measures on the wave 1 (2007) survey measures and 2006 Census measures.

Our other approach estimates these as simultaneous equations models (Berry 1984). Although we estimate these with a maximum likelihood estimator in Stata 13.1 in which all equations are estimated simultaneously in a single model, the intuition is identical to a two stage

[10] The 2006 census measures are included as covariates in each of these equations, as they are clearly temporally prior to the 2010 and 2012 survey waves.

least squares estimator using instrumental variables (for a complete discussion of this, see Paxton, Hipp, and Marquart-Pyatt 2011). For example, we can estimate collective efficacy (y_2) as a function of violence (y_1) at the same time period as:

(2) $$y_{1t} = \alpha_t + \Gamma_1 y_{1t-1} + \Gamma_2 WY_{t-1} + \Gamma_3 X_{t-1} + \varepsilon_{1t}$$

(3) $$y_{2t} = \alpha_t + \beta_1 y_{2t-1} + \beta_2 y\wedge_{1t} + B_3 WY_{t-1} + B_4 X_{t-1} + \varepsilon_{1t}$$

The first equation regresses violence at time *t* on violence at time *t-1* and the control variables (X) and the spatially lagged measures (WY). This provides an estimate of y_1 ($y_1\wedge$) at time *t* which is included in equation 3 (the structural equation of interest). Here, β_1 captures the effect of collective efficacy at one time point on collective efficacy at the next time point, and β_2 estimates the simultaneous effect of violence on collective efficacy at time *t*. These equations assume that the only effect of violence on collective efficacy is within the same time period; to be a suitable instrument, violence at time *t-1* must have no effect on collective efficacy at time *t* (other than its effect on the level of violence at time *t*). We are therefore assuming in this model that the effect of violence on collective efficacy is relatively short-term and there is no additional effect of violence from 2 years ago on collective efficacy once accounting for the current level of violence. A similar set of equations capture the simultaneous effect of collective efficacy on violence, and analogously assume that the level of collective efficacy 2 years ago does not impact violence once accounting for the current level of collective efficacy. This model is identified; for a discussion of this, see chapter 5 of (Finkel 1995).

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 then temporally lagged these spatially lagged measures, which mirrors the approach adopted by other studies (Hipp, Tita, and Greenbaum 2009; Bernasco and Block 2011; Steenbeek and Hipp 2011).

RESULTS

We first describe the results of the two wave cross-lagged model assuming a 2-3 year period for the causal effect (Figure 1b). Given the importance of collective efficacy in the recent neighborhoods and crime literature, we begin by focusing on the equation with collective efficacy as the outcome measure. In Table 2, we see strong stasis effects, as neighborhoods with higher levels of collective efficacy at one time point have higher levels of collective efficacy, on average, at the next time point (b=.72). There is no evidence in this model of a negative feedback effect of crime on the level of collective efficacy, as the coefficient for the violent crime rate is actually slightly positive, although not significant. Of the neighborhood characteristics, the one significant effect detected is for concentrated disadvantage: neighborhoods with one standard deviation higher concentrated disadvantage at one time point have about .21 standard deviations lower collective efficacy at the next time point (b=-.032), controlling for the other measures in the model. Furthermore, higher levels of concentrated disadvantage in the surrounding area also lead to lower collective efficacy at the next time point.

<<<Table 2 about here>>>

We next turn to the equation in which the violent crime rate is the outcome measure. There is no evidence that neighborhoods with higher levels of collective efficacy at one time point have lower levels of violent crime as reported by the police, as the coefficient is actually positive. Note that these models are accounting for the violent crime rate at the previous time point, and there is strong evidence that more violence at one time point is associated with higher levels of violence at the next time point. There is, however, strong evidence of a relationship between concentrated disadvantage and violence. Neighborhoods with one standard deviation higher concentrated disadvantage at one time point have .24 standard deviations more violent crime (b=.088; β=.24) at the next time point. There is also a spatial effect in which more young adults in the surrounding area lead to more violence at the next time point.

We next turn to the equations in which the neighborhood structural characteristics are the outcome measures. These equations test whether there are feedback effects from violence or collective efficacy on these measures. In the equation with concentrated disadvantage as the outcome measure, we find evidence that neighborhoods with one standard deviation higher violent crime at one time point have .32 standard deviations more concentrated disadvantage at the next time point. Thus, there appears to be a reciprocal relationship between concentrated disadvantage and violence in that both are impacting each other over time in this longitudinal analysis. We also see evidence in these models that neighborhoods with higher levels of collective efficacy at one time point have somewhat lower levels of concentrated disadvantage at the next time point (β=-.521, $p < .10$). Whereas higher levels of collective efficacy do not appear to impact the level of crime at the next time point directly, they do impact it indirectly by reducing the level of concentrated disadvantage (presumably through a selective mobility process). And neighborhoods surrounded by fewer young adults have higher levels of disadvantage at the next time point.

In the equation with residential instability as the outcome measure, we see no evidence that the level of violence, collective efficacy, or concentrated disadvantage impact the level of residential instability at the next time point. Finally, in the equation with language heterogeneity as the outcome measure, there is also no evidence that the level of violence, collective efficacy, or concentrated disadvantage impact this characteristic of neighborhoods. However, neighborhoods with more residential instability and more young adults experience larger increases in language heterogeneity by the next time point. Neighborhoods surrounded by higher levels of language heterogeneity are more likely to experience larger increases in language heterogeneity themselves. This indicates that there are spatially clustered locations of immigrants with higher levels of language heterogeneity, with increasing language heterogeneity over the period of this study. The fact that neighborhoods surrounded by more concentrated disadvantage and residential stability also experience an increase in language heterogeneity suggests that this broader spatial pattern impacts the location of where these immigrant communities develop.

Additional temporal patterns

We next assess the extent to which the results are different when assuming either a shorter temporal causal relationship (Table 3) or a longer temporal causal relationship (Table 4). In general, we find that our results are generally quite robust regardless of the assumption about the temporal causal period. For example, in none of the three models is there evidence of a negative feedback effect of violence on the level of collective efficacy, as the coefficient for violent crime is not significant in Tables 2, 3, and 4. Instead, concentrated disadvantage has an important impact on collective efficacy, as higher levels of concentrated disadvantage in the neighborhood or the surrounding area lead to lower collective efficacy regardless of the model specification.

<<<Tables 3 and 4 about here>>>

In the equation in which violence is the outcome measure, there is no evidence in any of these three models that neighborhoods with higher levels of collective efficacy result in lower levels of violence as reported by the police. In fact, the coefficient is significantly positive in the 2-year cross-lagged model (Table 2) and the simultaneous effect model (Table 3) and positive, but not significant, in the 5-year cross-lagged model (Table 4). Despite the body of evidence finding a negative relationship between collective efficacy and violence in cross-sectional analyses in Australia (Mazerolle, Wickes, and McBroom 2010) and elsewhere (Sampson, Raudenbush, and Earls 1997; Sampson and Wikstrom 2008), we find no evidence for this relationship when assessing it longitudinally regardless of the temporal assumption of the causal relationship. There is, however, strong evidence in all three models of a positive relationship between concentrated disadvantage and violence.

In all three models, higher levels of violence lead to higher levels of concentrated disadvantage. Thus, we see a robust reciprocal relationship between concentrated disadvantage and violence in that both are impacting each other over time—regardless of the specified temporal period—in this longitudinal analysis. There is some evidence that higher levels of collective efficacy lead to lower levels of concentrated disadvantage, although this process may occur over a longer period as the effect is only significant at $p < .05$ in the five year lag model. And there is a positive relationship between more 15 to 24 year olds in the surrounding area and concentrated disadvantage in the neighborhood when assuming a simultaneous or two-year causal relationship; the effect is weaker when assuming a 5-year causal relationship.

Whereas there is no evidence that that the level of violence, collective efficacy, or concentrated disadvantage impact language heterogeneity in neighborhoods, neighborhoods with more residential instability and more young adults experience larger increases in language heterogeneity in all three models. Likewise, neighborhoods surrounded by higher levels of language heterogeneity, concentrated disadvantage, and residential stability tend to experience larger increases in language heterogeneity. There is no evidence in any of these models that the level of violence, collective efficacy, or concentrated disadvantage impacts the level of residential instability in the neighborhood.[11]

Sensitivity analyses

In our main analytic models we focused on violent crime as a neighborhood outcome. A criticism is that this measure combines not only homicides, robberies, and aggravated assaults, but also simple assaults. Given the evidence of Baumer (2002) that simple assaults may be more susceptible to reporting bias, we estimated additional models for three crime types separately: aggravated assaults, robberies, and simple assaults (there were too few homicides to provide stable estimates). The general pattern of results was very similar to those already presented, and similar across these three separate crime types. There were only two differences worth noting. First, in both the cross-lagged and simultaneous models collective efficacy had a weaker positive relationship with the subsequent level of these three individual crime types compared to the

[11] Regarding model fit, for the two-year lag model (Table 2), the χ^2 of 173.2 on 73 df ($p < .01$) implies a nonperfect fit, although the RMSEA of .098 and the CFI of .945 suggest a reasonable approximate fit for this model. Simulation studies have shown that model fit can be impacted by various characteristics of the model, and therefore strictly employing cutoff values is not wise; nonetheless, rough guidelines includes RMSEA values below .08 and CFI values above .95 (Hu and Bentler 1999). Inspection of modification indices suggested only that estimating the effect of lagged violence on current violence should be freed over the two waves; when freeing this path, or constraining the error covariances at the same time point to be zero (given their nonsignificance), the model fit only improved somewhat (RMSEA = .081, CFI = .958), and, most importantly, the substantive results remained unchanged. It is important to recall the insights of Browne and colleagues (Browne, MacCallum, Kim, Andersen, and Glaser 2002) that model fit will be negatively impacted due to high statistical power when the R-squares of the equations are quite high, as they are here, ranging from .56 to .90. In the simultaneous effects model (Table 3) the fit was similar: χ^2 of 174.1 on 72 df ($p < .01$) implies a nonperfect fit, although the RMSEA of .10 and the CFI of .944 suggest a reasonable approximate fit for this model. Freeing the lagged violence effect and constraining the error covariances at the same timepoint to zero again resulted in modest improvement to model fit, but with the substantive results remaining unchanged. The 5-year lag model (Table 4) was exactly identified, and therefore model fit could not be assessed.

relationship with violent crime in general in the main models. Second, in these ancillary models collective efficacy had a stronger negative relationship with subsequent concentrated disadvantage for all three of these separate crime type models. Thus, we see no evidence that our results are impacted by combining these different crime types into a single measure of violence.

DISCUSSION

This study has contributed to the neighborhoods and crime literature by exploring the relationship between concentrated disadvantage, collective efficacy, and violence both longitudinally and spatially. Whereas there have been numerous studies exploring these characteristics of neighborhoods in cross-sectional designs, a longitudinal strategy is crucial for assessing whether collective efficacy indeed operates to reduce crime. As it is also plausible that levels of violence may reduce collective efficacy over time, teasing apart these possible reciprocal relationships is crucial. Given the lack of existing theoretical specificity about the time scale of these processes, an important contribution of this study was exploring three different model specifications of the temporal pattern of this relationship, rather than simply assuming that one is correct. The study was also able to account for the possible spatial patterning of these processes, and assess whether the composition of these measures nearby was related to changes in these measures in the neighborhood itself over time. This study failed to find any evidence that higher levels of collective efficacy in a neighborhood at one point in time are directly associated with greater decreases in violence over time. There was some evidence, however, that concentrated disadvantage plays an important role in linking the level of collective efficacy in a neighborhood with the level of violence.

A contribution of this study was exploring three possible time periods for these causal processes to operate. Given that existing theories are typically quite unclear on the temporal period over which these various processes ought to operate, we adopted an approach that tested three different possible lags rather than simply assuming that one of them was correct. It was reassuring to see that our results were quite robust over these three different temporal specifications. Thus, the relationship between violence and concentrated disadvantage was relatively similar regardless whether we used a simultaneous model, a 2-year lag, or a 5-year lag. Nonetheless, certain relationships appeared to operate only over a longer time scale: for example, the relationship between higher levels of collective efficacy at one time point at subsequently lower concentrated disadvantage was only statistically significant in the five-year lag model. Although our results were generally robust over these different temporal model specifications, the ecological crime literature would be well served to carefully consider the time period of these proposed causal relationships in future work.

One notable finding was the lack of a direct relationship between collective efficacy and violence over time. Whereas prior research has often found a cross-sectional relationship between collective efficacy and violence—including research using ACCS data (Mazerolle et al., 2010)—no such effect was found here in these longitudinal analyses. This is an important finding, given that cross-sectional models are a particularly weak assessment of potential causal relationships. We similarly found no relationship when estimating models assuming a longer or a shorter time period for this causal relationship. Although only a single study of one particular urban area, it does raise questions about the causal impact of this relationship and imply the need for additional longitudinal analyses. We attempted to assess different causal lags of this possible relationship, given the discussion of (Sampson 2012) regarding the distinction between enduring effects and situational effects of collective efficacy. Our simultaneous equations model was attempting to capture situational effects in which residents are able to intervene when observing possible instances of crime or disorder. Our 2- and 5-year lag models were attempting to capture enduring effects of collective efficacy.

Although a robust finding in the existing literature is the importance of concentrated disadvantage for levels of violence in neighborhoods, this study reinforces the importance of this reciprocal relationship in a longitudinal framework. In our study, higher levels of concentrated disadvantage had one of the strongest relationships with violence at later time points. This is consistent with longitudinal studies of this relationship in the U.S. (e.g., Hipp 2010; Kubrin and Herting, 2003). But at the same time, we found that higher levels of violence were the strongest predictor of increased concentrated disadvantage at the next time point. This reciprocal relationship is consistent with research from the U.S. (Hipp 2010) and implies a downward spiral for these neighborhoods. This reciprocal relationship was robust over our three different specifications of the temporal period of these processes.

It is interesting to note that we also detected a strong reciprocal relationship between collective efficacy and concentrated disadvantage over time, and there was a spatial patterning to this relationship. Concentrated disadvantage and collective efficacy in neighborhoods tended to move in opposite directions over time. Neighborhoods with more concentrated disadvantage at one point in time experienced a subsequent decrease in collective efficacy, and this relationship was robust to our three different model specifications of the temporality of this process. Furthermore, concentrated disadvantage in the surrounding area had an additional negative effect on residents' sense of collective efficacy, implying that spatially disadvantaged neighborhoods are particularly hard hit regarding their sense of an ability to work together. The fact that neighborhoods with higher levels of collective efficacy experienced lower levels of disadvantage over time has not been detected previously in the literature but speaks to the enduring effects of collective efficacy's presence, or absence (Sampson 2012); we emphasize that this relationship was not statistically significant in the models specifying a shorter time lag, but was only significant in the five-year lag model. This suggests that this may be a process that plays out more slowly, implying that it may not be detected in studies focusing on shorter time periods. Conversely, it appears that neighborhoods with lower collective efficacy experience larger increases in concentrated disadvantage over time, which then leads to greater increases in violence. This implies a possible different mechanism through which collective efficacy may impact crime in neighborhoods: a differential mobility pattern in the neighborhood that increases concentrated disadvantage, and then subsequently more violence. This indicates a dynamic relationship that requires further empirical exploration.

Another notable finding was the substantial clustering of ethnic diversity detected over time. Although ethnic clustering has been detected in other settings such as the U.S., it has only been detected in Australia within Sydney and Melbourne. Indeed, prior to the 2011 census Brisbane had the lowest concentration of immigrants when compared to Sydney, Melbourne and Perth (Markus, Jupp, and McDonald 2009). But in our study, neighborhoods surrounded by higher concentrations of immigrants were more likely to see an increase in immigrants themselves. But another interesting *non*-pattern was detected: this increased clustering of immigrants is not associated with negative consequences over time of any sort. Furthermore, there is no evidence that neighborhoods with more language heterogeneity experience greater increases in violent crime or greater decreases in collective efficacy over time.

We acknowledge four limitations of the current research design. First, although longitudinal data allows for exploring how these patterns change over time, it is nonetheless the case that we were constrained to discrete observation points that may or may not match the true causal process (Taylor 2015). We therefore used three different temporal specifications to assess the robustness of the results. Second, we were constrained to measuring these processes at the larger unit of analysis of neighborhoods. Although a growing body of research focuses on street segments (Groff, Weisburd, and Yang 2010; Weisburd, Bushway, Lum, and Yang 2004), we were limited to larger units given the challenge of collecting information on levels of collective efficacy in such small units (Weisburd, Groff, and Yang 2012). Third, our obtained sample over-represented certain types of households in the neighborhood and therefore may have affected our collective efficacy measure. We attempted to account for this with an ecometrics approach that corrects for the biases of certain types of persons (Sampson and Raudenbush 1999), but this possible limitation should be kept in mind. Fourth, although we had a measure of collective efficacy, we had no measures of actual informal social control behavior in these neighborhoods to assess whether it might impact violence over time (Steenbeek and Hipp 2011). This is a limitation of many studies in the collective efficacy literature, as they are reliant upon the assumption that these perceptions of collective efficacy indeed lead to collective action on the part of residents. It is possible that the more proximate mechanism associated with crime rates is what residents do when presented with a problem in their neighborhood.

Although we did not find a direct relationship between collective efficacy and violence over time, existing theory presumes that shared perceptions of collective efficacy lead to informal actions to reduce crime. For example, Reynald (2009) argues that although residents may be available and willing to supervise their environment, they must also able to take direct action (such as contacting the police or directly intervening to stop the incident) to prevent crime. We believe unpacking the relationship between collective efficacy, citizen oriented actions and crime, and how this might unfold over time, is the next frontier for ecology of crime scholarship.

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Tables and Figures

Table 1. Summary statistics of variables used in analyses

	Wave 1		Wave 2		Wave 3		Change W1-W3	
	Mean	SD	Mean	SD	Mean	SD	SD	RLCV
Dependent variable:								
Logged violent crime rate	0.549	0.373	0.572	0.379	0.532	0.367	0.139	37.9%
Independent variables:								
Collective efficacy	0.008	0.140	0.019	0.149	0.017	0.157	0.087	55.1%
Concentrated disadvantage	0.000	1.000			0.000	1.000	0.456	45.6%
Residential instability	42.297	8.910			38.173	10.292	7.711	74.9%
Language heterogeneity	0.181	0.098			0.124	0.108	0.067	62.2%
Percent aged 15 to 24	13.972	2.829			14.028	2.878	1.596	55.4%
Spatial lag variables:								
Concentrated disadvantage	0.000	1.000			0.000	1.000	0.396	39.6%
Residential instability	42.571	3.781			38.137	5.298	3.237	61.1%
Language heterogeneity	0.186	0.064			0.125	0.080	0.041	51.0%
Percent aged 15 to 24	14.484	2.433			14.264	1.974	1.019	51.6%

N= 148 neighborhoods. RLCV: ratio of longitudinal to cross-sectional variance in measure

Table 2. Three-wave longitudinal models for Brisbane, using combined collective efficacy measure, including spatial lag measures. Testing cross-lagged effects of collective efficacy and violence

	(1)		(2)		(3)		(4)		(5)	
	Collective efficacy		Violent crime		Concentrated disadvantage		Residential instability		Language heterogeneity	
Collective efficacy (t-1)	0.720	**	0.254	*	-0.521	†	-7.660		-0.061	
	(14.13)		(2.15)		-(1.65)		-(1.14)		-(1.30)	
Violent crime (t-1)	0.011		0.822	**	0.567	**	-1.055		-0.003	
	(1.55)		(37.35)		(9.15)		-(0.79)		-(0.33)	
Concentrated disadvantage (t-1)	-0.032	**	0.088	**	0.704	**	0.638		0.003	
	-(4.79)		(5.11)		(15.75)		(0.67)		(0.50)	
Residential instability (t-1)	0.000		-0.003	†	0.003		0.762	**	0.001	*
	-(0.29)		-(1.93)		(0.83)		(10.46)		(2.47)	
Language heterogeneity (t-1)	-0.054		-0.160		-0.079		-7.196		0.544	**
	-(0.91)		-(0.99)		-(0.23)		-(0.99)		(10.72)	
Percent aged 15 to 24 (t-1)	-0.003		0.007		0.010		0.322		0.006	**
	-(1.40)		(1.54)		(0.71)		(1.14)		(3.26)	
Population density (t-1)	0.001		-0.002		0.006		-0.111		0.000	
	(1.59)		-(1.06)		(1.07)		-(1.00)		-(0.51)	
Nearby concentrated disadvantage (t-1)	-0.012	*	-0.006		0.059		-0.205		0.016	**
	-(2.16)		-(0.42)		(1.58)		-(0.26)		(2.88)	
Nearby residential instability (t-1)	-0.001		-0.005	†	-0.007		0.315		-0.003	*
	-(0.96)		-(1.71)		-(0.79)		(1.61)		-(2.38)	
Nearby language heterogeneity (t-1)	-0.112		0.031		-0.732		5.190		0.573	**
	-(1.26)		(0.13)		-(1.30)		(0.44)		(6.93)	
Nearby aged 15 to 24 (t-1)	-0.001		0.015	*	-0.042	*	0.302		0.003	
	-(0.24)		(2.08)		-(2.43)		(0.82)		(1.22)	
Intercept	0.097	†	0.096		0.565		-14.048		-0.125	†
	(1.86)		(0.71)		(1.23)		-(1.43)		-(1.84)	
R-square	0.74		0.90		0.89		0.56		0.82	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. N=148 neighborhoods*

Table 3. Three-wave longitudinal models for Brisbane, using combined collective efficacy measure, including spatial lag measures. Testing simultaneous effects of collective efficacy and violence

	(1)		(2)		(3)		(4)		(5)	
	Collective efficacy		Violent crime		Concentrated disadvantage		Residential instability		Language heterogeneity	
Collective efficacy (t)			0.367	*						
			(2.03)							
Collective efficacy (t-1)	0.711	**			-0.517		-7.819		-0.061	
	(13.63)				-(1.64)		-(1.16)		-(1.30)	
Violent crime (t)	0.014									
	(1.44)									
Violent crime (t-1)			0.816	**	0.565	**	-1.077		-0.003	
			(36.03)		(9.11)		-(0.81)		-(0.35)	
Concentrated disadvantage (t-1)	-0.033	**	0.100	**	0.705	**	0.640		0.003	
	-(4.68)		(4.65)		(15.82)		(0.68)		(0.52)	
Residential instability (t-1)	0.000		-0.003	†	0.003		0.762	**	0.001	*
	-(0.20)		-(1.94)		(0.81)		(10.43)		(2.46)	
Language heterogeneity (t-1)	-0.054		-0.142		-0.081		-7.261		0.543	**
	-(0.91)		-(0.86)		-(0.24)		-(1.00)		(10.71)	
Percent aged 15 to 24 (t-1)	-0.003		0.008	†	0.010		0.320		0.006	**
	-(1.45)		(1.66)		(0.72)		(1.14)		(3.26)	
Population density (t-1)	0.001		-0.002		0.005		-0.113		0.000	
	(1.60)		-(1.18)		(1.05)		-(1.02)		-(0.53)	
Nearby concentrated disadvantage (t-1)	-0.012	*	0.000		0.059		-0.211		0.016	**
	-(2.15)		-(0.02)		(1.59)		-(0.27)		(2.88)	
Nearby residential instability (t-1)	-0.001		-0.005		-0.007		0.315		-0.003	*
	-(0.92)		-(1.56)		-(0.78)		(1.61)		-(2.38)	
Nearby language heterogeneity (t-1)	-0.108		0.062		-0.727		5.304		0.574	**
	-(1.20)		(0.25)		-(1.30)		(0.45)		(6.94)	
Nearby aged 15 to 24 (t-1)	-0.001		0.015	*	-0.042	*	0.309		0.003	
	-(0.33)		(2.06)		-(2.41)		(0.84)		(1.23)	
Intercept	0.098	†	0.068		0.559		-14.101		-0.126	†
	(1.86)		(0.46)		(1.21)		-(1.43)		-(1.84)	
R-square	0.74		0.90		0.89		0.56		0.82	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. N=148 neighborhoods*

Table 4. Two-wave longitudinal models for Brisbane, using combined collective efficacy measure, including spatial lag measures. Testing cross-lagged effects of collective efficacy and violence between waves 1 and 3

	(1)		(2)		(3)		(4)		(5)	
	Collective efficacy		Violent crime		Concentrated disadvantage		Residential instability		Language heterogeneity	
Collective efficacy (t-2)	0.626	**	0.130		-0.719	*	-0.274		-0.050	
	(8.74)		(0.65)		-(2.45)		-(0.04)		-(1.13)	
Violent crime (t-2)	0.006		0.768	**	0.437	**	0.352		0.003	
	(0.55)		(25.29)		(9.80)		(0.36)		(0.38)	
Concentrated disadvantage (t-1)	-0.037	**	0.094	**	0.728	**	1.052		0.005	
	-(3.90)		(3.56)		(18.68)		(1.24)		(0.83)	
Residential instability (t-1)	-0.001		-0.003		-0.001		0.783	**	0.001	**
	-(0.66)		-(1.41)		-(0.28)		(11.09)		(2.67)	
Language heterogeneity (t-1)	-0.124		-0.187		-0.131		-6.488		0.547	**
	-(1.51)		-(0.82)		-(0.39)		-(0.88)		(10.78)	
Percent aged 15 to 24 (t-1)	-0.006	†	0.002		0.008		0.351		0.006	**
	-(1.85)		(0.25)		(0.60)		(1.23)		(3.09)	
Population density (t-1)	0.001		-0.001		0.003		-0.126		-0.001	
	(1.06)		-(0.30)		(0.59)		-(1.16)		-(0.89)	
Nearby concentrated disadvantage (t-1)	-0.020	*	-0.012		0.064	†	-0.136		0.015	**
	-(2.24)		-(0.48)		(1.75)		-(0.17)		(2.78)	
Nearby residential instability (t-1)	-0.001		-0.012	†	-0.011		0.369	†	-0.003	*
	-(0.64)		-(1.93)		-(1.26)		(1.90)		-(2.19)	
Nearby language heterogeneity (t-1)	-0.133		-0.147		-0.829		5.777		0.584	**
	-(0.98)		-(0.39)		-(1.50)		(0.48)		(6.98)	
Nearby aged 15 to 24 (t-1)	0.004		0.014		-0.027		0.406		0.004	†
	(1.08)		(1.22)		-(1.63)		(1.13)		(1.71)	
Intercept	0.141		0.515	†	0.754	†	-19.931	*	-0.155	*
	(1.37)		(1.79)		(1.79)		-(2.17)		-(2.44)	
R-square	0.78		0.87		0.91		0.55		0.83	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. N=148 neighborhoods*

Figure 1a

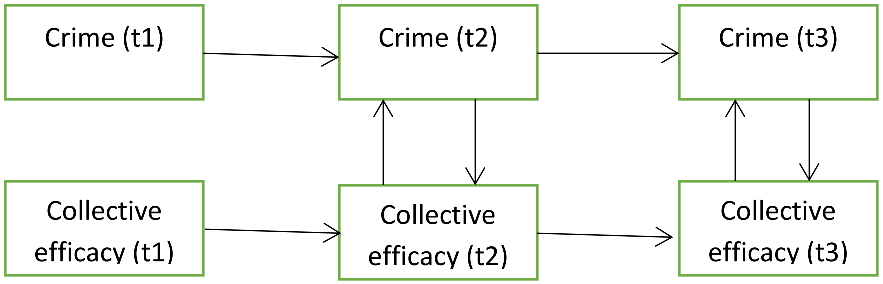


Figure 1b

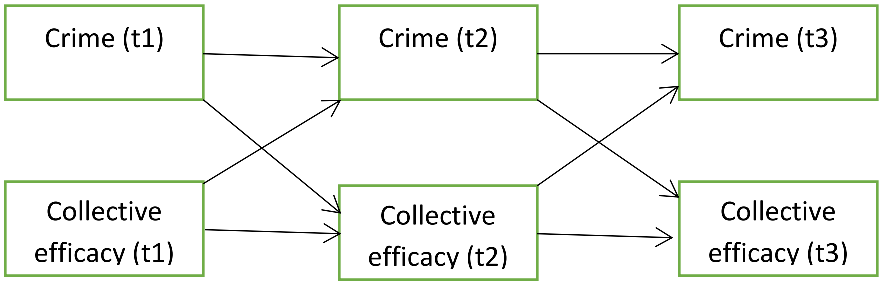
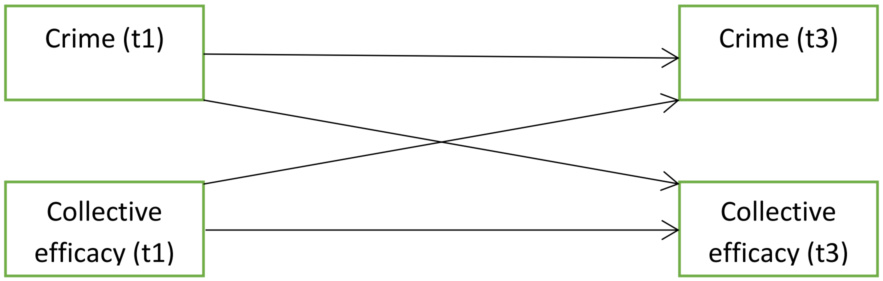


Figure 1c



Appendices

Appendix 1.Resident population size for ACCS suburbs and sample size by wave and cohort.

	Average No. of Residents	Min	Max	ACCS Long-itudinal Sample N	Top-Up Sample N	Total Sample N
ACCS Wave 2	5690	245	20999	1077	3247	4324
ACCS Wave 3	6046	241	21001	2286	1935	4221
ACCS Wave 4	6633	258	22807	2473	1659	4132

Appendix 2. ABS Census and ACCS sample demographics

Demographics	**Census 2006**	**Census 2011**	**ACCS Wave 2**	**ACCS Wave 3**	**ACCS Wave 4**
Age	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%
Language other than English					
English Only	85.3%	83.7%	93.3%	89.0%	93.8%
Non English	8.9%	11.0%	6.7%	11.0%	6.2%
Country of Birth					
Born in Australia	73.4%	72.4%	75.5%	75.9%	75.6%
Employment					
Employed (full time)	39.7%	39.0%	42.0%	38.5%	37.1%
Employed (part time)	17.5%	18.1%	20.5%	19.2%	18.3%
Unemployed	2.7%	3.7%	2.1%	3.1%	3.5%
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%
Income					
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%

Appendix 3. Comparison of neighborhood characteristics for ACCS suburbs compared to state and national averages

	2001			**2006**			**2011**		
	ACCS	**QLD**	**AUST**	**ACCS**	**QLD**	**AUST**	**ACCS**	**QLD**	**AUST**
% Unemployed	4.8%	8.2%	7.4%	2.8%	4.7%	5.2%	3.8%	6.1%	5.6%
% Renting	25.2%	31.6%	27.6%	23.0%	30.0%	27.2%	23.1%	32.0%	28.7%
% ATSI	1.5%	3.1%	2.2%	1.6%	3.2%	2.3%	1.9%	3.6%	2.5%
% Born Overseas	20.8%	16.9%	21.6%	26.9%	17.58%	22.0%	24.4%	20.2%	24.4%
% LOTE	8.7%	6.9%	15.0%	10.0%	7.6%	15.7%	12.4%	9.3%	18.0%
Median Household Income	$929	$739	$784	1225	$1036	$1029	$1559	$1227	$1230

Appendix 4. Items from the Collective Efficacy Scale from Waves 2, 3 and 4 of the ACCS.

The Collective Efficacy adapted from the Project of Human Development in Chicago Neighborhoods	
Willingness to Intervene	• If a group of community children were skipping school… • If some children were spray painting graffiti… • If there was a fight in front of your house • If a child was showing disrespect… • Suppose that because of budget cuts the fire station… Response categories: Very unlikely, unlikely, neither likely/unlikely, likely, very likely
Social Cohesion and Trust	• People in this community are willing to help their neighbors • This is a close-knit community • People in this community can be trusted • People in this community do not share the same values Response Categories: Strongly disagree, disagree, neither agree nor disagree, agree, strongly agree

Figure A1. Full path model showing crime (c), disadvantage (d), and collective efficacy (ce)