Accepted Manuscript

The resilience of neighborhood social processes: A case study of the 2011 Brisbane flood

Rebecca Wickes, Chester Britt, Lisa Broidy

PII: S0049-089X(16)30060-6

DOI: 10.1016/j.ssresearch.2016.07.006

Reference: YSSRE 1951

To appear in: *Social Science Research*

Received Date: 4 February 2016

Revised Date: 14 May 2016

Accepted Date: 12 July 2016

Please cite this article as: Wickes, R., Britt, C., Broidy, L., The resilience of neighborhood social processes: A case study of the 2011 Brisbane flood, *Social Science Research* (2016), doi: 10.1016/j.ssresearch.2016.07.006.

The resilience of neighborhood social processes:

A case study of the 2011 Brisbane Flood

Rebecca Wickes*
School of Social Science
The University of Queensland

Chester Britt
Department of Sociology
Iowa State University

Lisa Broidy
Griffith Criminology Institute
Griffith University

Running Head: The impact of disasters on neighborhood processes

*Corresponding Author

Rebecca Wickes
School of Social Science
The University of Queensland
St. Lucia Campus, Qld 4072
Australia
P: +617-3365-2204
E: **r.wickes@uq.edu.au**

Acknowledgements: This work was supported by the Australian Research Council (LP0453763; DP0771785; RO700002; DP1093960; DP1094589 and DE130100958).

Author Information:

Rebecca Wickes is an ARC Research Fellow and 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 focuses 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.

Chester Britt is a Professor and Chair of the Department of Sociology at Iowa State University. He is a past Editor of *Justice Quarterly*. His research interests include criminological theory, criminal justice decision-making, and quantitative methods. He is co-author (with David Weisburd) of *Statistics in Criminal Justice* (4th ed.). His research has been published in journals, such as, *Journal of Quantitative Criminology*, *Justice Quarterly*, and *Law and Society Review*.

Lisa Broidy is an Associate Professor in the School of Criminology and Criminal Justice at Griffith University and a member of the Griffith Criminology Insitute. Broadly, her research focuses on the etiology of crime with a particular focus on the influence of gender, life course transitions, institutional contact, and strains (including victimization and trauma). Her research has been published in a variety of peer-reviewed journals including *Criminology, Social Forces, Journal of Research in Crime and Delinquency, Homicide Studies* and *Justice Quarterly.*

The resilience of neighborhood social processes:

A case study of the 2011 Brisbane Flood

Abstract

Social disorganization theories position neighborhood social capital and collective efficacy as key social processes that should facilitate community resilience in the aftermath of disaster. Yet limited evidence demonstrates that these social processes are themselves resilient with some studies showing that disaster can fracture even once cohesive neighborhoods. In this paper we assess the stability of neighborhood level collective efficacy and social capital before and after a disaster. We use multilevel structural equation modeling and draw on census and longitudinal survey data collected from over 4000 residents living in 148 neighborhoods in Brisbane, Australia before and after a significant flood event. We examine what happens to social capital and collective efficacy in flooded and non-flooded neighborhoods and assess whether demographic shifts are associated with change and/or stability in these processes. We find strong evidence that these processes operate similarly across flooded and not flooded communities. Our findings also reveal significant stability for our measures of social capital across time, while collective efficacy increases post flood across all neighborhoods, but more so in flooded neighborhoods. Neighborhood demographics have limited effect on patterns of stability or change in these social processes. We discuss the theoretical and practical implications of these findings for our understanding of neighborhood resilience in the wake of disaster.

Key Words: Collective Efficacy, Social Capital, Disaster, Resilience, Neighborhoods

1.0 Introduction

With increases in the number and intensity of extreme weather events predicted for the coming decades (Huppert and Sparks, 2006, Van Aalst, 2006), there is a pressing need to ensure that vulnerable areas are prepared for the associated short- and long- term effects of these disasters. Scholarship highlights the key role of a community's social and structural resources and their association with disaster resilience. Geographic communities with high levels of social capital, collective efficacy and access to socio-economic resources are hypothesized to fare significantly better in the post-disaster context (Norris et al., 2008). Policy makers and practitioners have taken note of this. Implementation plans for disaster preparedness often aim to build community resilience in the pre-disaster context in an effort to minimize disaster vulnerability and promote effective collective responses should disaster hit (Cutter et al., 2010). In fact, building or augmenting 'collective readiness' in disaster quiescence has become a major policy initiative around the globe. But will this work? Even if local social processes can be enhanced before a disaster, how resilient are these social resources in the context of an actual disaster? The evidence in support of strategies to augment the social processes associated with collective readiness is far from conclusive.

Though levels of neighborhood poverty are relatively stable over time, most residents living in persistently disadvantaged neighborhoods still prioritize community safety and security and can work together to solve local problems (Sampson, 2012; Sampson, Raudenbush and Earls, 1997). Thus while the resources necessary to reduce neighborhood disadvantage are vast and part of a long-term project, enhancing neighborhood social processes by increasing available community social capital or strengthening a community's collective efficacy, is potentially achievable through shorter-term initiatives. However, we know little about the conditions that promote, sustain or deteriorate neighborhood social processes. Certainly cross-sectional research reveals that communities with high levels of social capital and collective efficacy have fewer self-reported health issues, higher levels of well-being and experience less crime and disorder (Browning and Cagney, 2002; Drucker et al., 2003; Hendryx and Ahern, 2001; Israel, Beaulieu and Hartless, 2001; Kawachi et al., 1997; Mazerolle, Wickes and McBroom, 2010; Noguera, 2001; Sampson, Raudenbush, and Earls, 1997). But few studies consider the durability of these neighborhood processes over time under normal conditions (for exceptions see Markowitz et al., 2001; Sampson, 2012; Steenbeek and Hipp, 2011). No study has examined the durability of these processes across communities after a significant shock, despite their theorized importance to well-being in the post disaster context (Breton, 2001; Kimhi and Shamai, 2004; Magis, 2010; Norris et al., 2008). Thus social processes remain the “black box” of the social sciences (Sampson, 2012:46) and we simply do not know if the social processes deemed necessary for disaster recovery and resilience can stand up to exogenous threats.

To better understand how local neighborhoods can successfully navigate their recovery from natural disasters and to provide an evidence base for policy and practice, we need to first assess the stability of key neighborhood processes over time and their durability in response to neighborhood stressors like natural disasters. This is the central aim of the current research. Drawing on census and longitudinal survey data collected from over 4000 residents before and after a significant flood event in Brisbane, Australia, we consider the sustained impact of the flood on neighborhood social capital and collective efficacy processes across 148 neighborhoods.

Our novel study addresses a significant lacuna in neighborhood effects research. Although there is a strong association between neighborhood social capital, collective efficacy and a range of social outcomes, our understanding of how these social processes *evolve* over time remains limited (Sampson, 2012). Access to pre- and post-disaster measures of neighborhood social processes therefore offers a unique opportunity to examine their stability and assess the degree to which they hold up under considerable stress. Importantly, our study provides an evidence base for disaster preparedness policy. Disaster policy initiatives cannot readily impact intractable neighborhood poverty, however, if neighborhood social processes can be augmented to withstand stressors, policy initiatives to build these processes may assist even structurally disadvantaged communities to more effectively respond to the local problems and challenges that accompany disaster. Further, by identifying the neighborhood demographic changes that weaken or strengthen these social processes over time, we can consider ways to mitigate the impact of population shifts (that occur after a disaster) on levels of social capital and collective efficacy in the post disaster context.

In what follows we provide a brief review of the neighborhood processes central to our study: social capital and collective efficacy. We discuss the limited scholarship that has considered stability and change in these neighborhood processes in the broader social science literature and in the disaster literature. As we are interested in the resilience of neighborhood social processes over time, we focus our discussion predominantly on those studies that have investigated these processes at the level of the neighborhood or local geographic community. We then provide further information on the Brisbane flood event and describe the ACCS survey, our variables of interest and our analytic strategy. We conclude with an overview of our results and the implications of our study for understanding stability and change in community social processes both prior to disaster and in its aftermath.

2.0 Literature Review

The geographic concentration of social problems is well documented in the literature. Since the mid-1800's, scholarship has demonstrated the clustering of crime, delinquency, child health, well-being and disease (Brooks-Gunn et al., 1993; Diez-Roux et al., 1997; Lochner et al., 2003; Sampson et al., 1997; Shaw and McKay, 1942). Several consistent findings characterize this body of work (Sampson, 2012; Sampson et al., 2002). To begin, we know neither poverty nor wealth is randomly distributed across a city's landscape. In many cities there is significant socio-economic clustering alongside racial/ethnic segregation, with disproportionate numbers of minority residents living in poorer areas (Krivo and Peterson, 2000; Peterson and Krivo, 1999; Peterson, Krivo, and Hagan, 2010). Further, a range of social problems characterizing these poor and segregated communities serve to reinforce their disadvantage (Krivo and Peterson, 2000; Peterson and Krivo, 1999). At the same time, more affluent areas enjoy substantial educational and employment opportunities that facilitate continued prosperity (Sampson et al., 2002).

Natural disasters are also geographically clustered but they impact all neighborhoods in an *ecologically* vulnerable area irrespective of socio-economic resources (Beck, 1992). Sociological definitions of disaster suggest that they are discrete events observable in a specific time and place and characterized by physical damages and losses coupled with disruptions in routine community functioning (Kreps, 1984:312). They are also events that require "unplanned courses of action" in order to respond to the crisis (Quarantelli, 2000:682; see also Quarantelli, 1989). At the same time, scholarship recognizes that natural disasters are not just singular events, but are social processes that reflect social resources and vulnerabilities (Cope et al., 2013; Perry and Quarantelli, 2005; Quarantelli, 1989). Thus the extent to which a geographical area can demonstrate resilience following a disaster largely depends on the local context in which a disaster occurs. As Browning and his colleagues (2006: 662) argue, disasters "must be understood in the context of socially produced conditions of vulnerability" (see also Gill, Picou and Ritchie, 2012). While affluent and disadvantaged communities may be equally likely to experience a disaster, the long term effects of a disaster vary greatly across place and this variation is largely due to the pre-disaster characteristics of the local area or the degree of social vulnerability in the pre flood context (Cutter, 1996, Cutter et al., 2003, Nilson, 1985; Perry and Lindell, 2003). Simply put, the more socially vulnerable an area is, the greater the impact of a disaster will be.

Social vulnerability is often determined by the presence or absence of a range of demographic characteristics that typically relate to "physical location and social class" (Gill, Picou and Ritchie, 2012:7). As Gotham and Greenberg (2014) suggest, spatially structured racial and economic inequalities are particularly important for understanding disaster recovery and resilience. For example, disaster areas exist on spectrum where "the more socially disadvantaged (i.e. vulnerable) can be contrasted with the more socially advantaged (i.e. resilient)" (Cope et al., 2013:873). Certainly the structural advantages that characterize affluent communities may reduce their vulnerability to disaster (Cutter et al., 2003, 2010; Norris et al., 2008; Norris, Sherrieb and Galea, 2010), but alone they cannot explain disaster resilience. Indeed, some poor neighborhoods may fare better than others post-disaster and the same can be said of wealthier neighborhoods (Aldrich, 2012; Norris et al., 2008). As disaster scholars note, this implicates neighborhood social processes as central to community resilience (Gill, Picou and Ritchie, 2012; Norris et al., 2008; Richie, 2004; Ritchie and Gill, 2007).

2.1 The Social Processes Central to Community Well-being

In the community resilience literature, neighborhood social capital and collective efficacy are strongly linked to neighborhood functioning in a post-disaster context (Breton, 2001; Kimhi and Shamai, 2004; Magis, 2010; Norris et al., 2008; Patterson, 2002). In the broader sociological scholarship, they are strongly associated with collective well-being and the absence of social problems (Coleman, 1988, Putnam, 2000; Putnam, 2007; Sampson, Raudenbush and Earls, 1997; Sampson, 2012).

Social capital is a central feature of social organization, and is often described as a social good, though this is not always the case.[1] Broadly, neighborhood level social capital refers to the social networks that characterize a given neighborhood and the norms and benefits that emerge from these networks. The primary functions of social capital are to facilitate strong social networks and develop shared norms and a working trust of local institutions and people (Coleman, 1988, 1990; Putnam, 2000). Social networks are particularly important for neighborhood resilience (Breton, 2001; Kimhi and Shamai, 2004; Magis, 2010; Norris et al., 2008; Patterson, 2002). Kirschenbaum (2004:101) suggests that social networks allow for the sharing of information about past survival behavior, provide the resources necessary to cope post-disaster, and act as a "crucial bridge in a complex communication link affecting disaster behaviors" (see also Hurlbert et al., 2001). Further, social networks are important for perceptions of social cohesion, coordination, support and care, and thus enable communities to respond to change or adversity while retaining core functions (Barrera, 1986; Paton and Johnston, 2001). When social networks are damaged or weakened as a result of external shock or disaster, the consequences can be significant. This is clearly illustrated in the longitudinal study of Cordova, Alaska after the Exxon Valdez oil spill. Ritchie and her colleagues found that the loss of social networks and the norms and benefits that come from living in a socially cohesive community hindered community resilience (Gill, Picou and Ritchie, 2012; Ritchie, 2004). As Richie and Gill (2010:75) argue, the "social capital loss spiral" that occurred after the oil spill led to greater levels of "individual stress and collective trauma".

[1] We note that social capital can also have a dark side. For example, for some communities strong kith and kinship ties may impede the ability to stem disorder (Pattillo, 1998); serve to exclude those who do not belong or foster a parochial culture that does little to assuage the effects of poverty (Wilson, 1987). Additionally, the advance of social capital is not without its critics. Some argue the conceptualization of social capital is ambiguous and often tautological (see Portes, 1998; Portes and Vickstrom, 2011).

Collective efficacy is linked to social capital and refers to the agentic capacity of communities to respond to and learn from challenges or threats to the neighborhood. Albert Bandura (1986/1997) first defined collective efficacy 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, p. 477: emphasis in original). In the late 1990s, Robert Sampson and his colleagues demonstrated the relevance of collective efficacy for explaining the differential ability of neighborhoods to prevent crime and disorder (Sampson et al., 1997). In contemporary cities, where neighbors are acquaintances at best, Sampson (1999) argued that the village model of strong ties underpinning much of the social capital literature needed revision. While not dismissing the importance of social capital, Sampson (2001) argued that social networks need to be activated to reduce neighborhood problems.

In the disaster literature, there is some evidence that perceptions of collective efficacy enhance disaster responses and disaster mitigation for individuals, though only one study examines neighborhood collective efficacy in a pre-disaster environment. Benight (2004) examined the degree to which an individual's own perception of neighborhood collective efficacy influenced the impact of resource loss after a flooding event. Individuals who perceived low collective efficacy were more adversely affected by resource loss than those with a high perception of collective efficacy. A study in Taiwan examined the relationship of collective efficacy with preparedness for a medical crisis and victim support. Individuals reporting higher collective efficacy were more likely to report that the neighborhood was prepared for the SARS outbreak and were also more likely to report satisfaction with the care of SARS victims (Fong and Chang, 2011). Paton and his colleagues (2010, p. 194) also found collective efficacy to be significantly and positively related to both the "formulation of risk beliefs and mitigation strategies" across three countries (Indonesia, New Zealand and Japan). In Australia, individuals with lower expectations pre-disaster reported lower collective efficacy post-disaster (Fay-Ramirez, Antrobus and Piquero, 2015). In the only neighborhood level study with access to survey data on social processes in a pre-disaster context, Browning et al. (2006) found that prior levels of collective efficacy did not exert protective effects on mortality rates after the 1995 Chicago heat wave. This may reflect damages to collective efficacy in the wake of the flood, but the data did not include post-flood measures of collective efficacy with which to assess this, or other temporally-based explanations for the findings.

2.2 Stability and Change in Neighborhood Social Processes

From the above discussion, the links between social capital, collective efficacy and neighborhood resilience are important. Yet our understanding of this relationship relies primarily on studies undertaken in the post-disaster context. We know little about the stability of these neighborhood level processes over time, particularly in the wake of a significant shock. Without this information we are unable to objectively assess the extent to which changes in these social processes occur as a function of a disaster. Thus while social capital and collective efficacy may be limited in some communities post disaster, we are cannot say that these apparent deficiencies in resiliency processes are quantitatively distinct from pre-disaster levels.

Further, neighborhood social processes are strongly influenced by the structural characteristics of the neighborhood like poverty and racial composition. Under regular conditions these structural characteristics exhibit significant consistency over time (Sampson, 2012). Even in micro places like street segments, there is notable stability in place-based socio-demographic characteristics (Weisburd, Groff and Yang, 2012). To the degree that neighborhood social processes are related to neighborhood level socio-demographics, we might expect similar levels of stability, however, there is scant empirical evidence to confirm this assumption. As a result of the limited availability of neighborhood level panel data, only three studies examine the stability and change of social processes across two or more time points. This research indicates that social cohesion and collective efficacy are stable over time, but are sensitive to changes in socio-demographic structures of neighborhoods. Drawing on panel and census data from 74 neighborhoods in the Netherlands over six time periods, covering 10 years, Steenbeek and Hipp (2011) find that while there was considerable variation between neighborhoods, within neighborhood variation in social cohesion was limited. Correlations for social cohesion over time ranged from 0.876 to 0.962 thus showing significant consistency. In the U.K., Markowitz and his colleagues (2001) also find stability in social cohesion over time. Similarly, looking across 80 neighborhoods in Chicago, there was limited change in collective efficacy across two time periods[2] (Sampson, 2012). Yet change does occur in both social-structural characteristics and social processes. When disadvantage increases, there may be a concomitant decrease in social processes important for social organization. For example, Steenbeek and Hipp (2011) find a significant and negative relationship between ethnic heterogeneity and social cohesion: as ethnic heterogeneity increases, social cohesion decreases.

These results provide some support that changes to the socio-demographic composition of the neighborhood can trigger changes in neighborhood processes, however, these changes are likely to be gradual and cumulative. Disasters, on the other hand, can bring about swift and significant changes in affected areas. The population composition can change dramatically in the days, weeks and months following a disaster: residents may perish or leave the neighborhood, housing prices and property values diminish in disaster affected areas, and infrastructure damage and job losses in particular communities may become permanent (Bin and Polasky, 2004; Elliott and Pais, 2006; Zottarelli, 2008). Compositional

[2] At the time of writing, there are no studies that consider the stability of social networks across time and place.

changes may have deleterious consequences for the neighborhood processes important for engendering resilience, and those changes may be immediate and consequential for the affected population. Moreover, these changes may become endemic, leading to long term changes in neighborhood capacity that have sustained implications for neighborhood health and well-being.

Few studies have examined the impact of disruptive events like a disaster or other exogenous shocks on levels of social capital or collective efficacy. The unexpected nature of disasters renders pre- and post- disaster comparisons exceptionally difficult, limiting the availability of data on neighborhood functioning before and after a disruptive event. Those studies that position social capital or collective efficacy as central to neighborhood resilience in the wake of such an event rely on a) proxy census variables to assess changes to social processes pre- and post-disaster; b) data documenting the impact of networks, social cohesion and trust on preparedness behaviors or risk assessments (as opposed to actual disaster response); c) post event recollections of pre-disaster neighborhood capacity (Hawkins and Maurer, 2010; Kim and Kang, 2010; LaLone, 2012; Mullins and Soetanto, 2013; Murphy, 2007; Richie, 2004; Richie and Gill, 2007); or d) focus on individual level assessments of collective efficacy (Fay-Ramirez, Antrobus and Piquero, 2015).

Case studies of disaster-affected communities provide mixed evidence regarding the stability or mutability of social processes following a disaster event. Early studies of disasters suggest they have a largely negative influence on local connections and a sense of neighborhood. The 1972 Buffalo Creek flooding that occurred in West Virginia destroyed the local communities living along the creek. With over 4,000 of the 5,000 residents left homeless and evacuated elsewhere, the “old bonds of kinship and neighborhood, which had always depended on physical proximity, were effectively severed” (Erikson, 1976, p.: 303). This fracturing of the neighborhood was associated with the emergence of various social problems like alcoholism, increased drug taking and youth delinquency. Others find that the majority of people behave in rational, constructive ways following a disaster (Goltz, Russell and Bourque, 1992; James and Wegner, 1980; Johnson, Feinberg and Johnston, 1994; Quarantelli and Dynes, 1977; Lindell, Tierney, and Perry, 2001). At least in the immediate period following a natural disaster, what emerges is what some have called an altruistic or therapeutic neighborhood (Barton, 1970; Fritz, 1968). Yet the persistence of the altruistic neighborhood beyond the immediate disaster response period is unlikely, especially in areas with lower levels of trust and connections prior to the disaster (Nilson, 1985; Perry and Lindell, 2003).

To date, only two studies have pre- and post- disaster measures of social capital and collective efficacy at the level of the neighborhood. Sweet (1998) examined changes in social relations and social cohesion before and after an ice storm in a rural neighborhood in northern New York State. Respondents reported that friends and neighbors extended a great amount of help immediately following the storm. Further, Sweet (1998) found that the mobilization of neighborhood networks increased levels of social cohesion in the immediate aftermath of the disaster, though he reported few lasting effects over time. Another study examined the impact of the 2007 Virginia Tech shooting. Hawdon and colleagues (2010) found a surge of social solidarity among students and academic staff at the college after the shooting, however, over subsequent waves of the survey, solidarity decreased and returned to pre-disaster levels.

2.3 The Present Study

The Brisbane flood event serves as a natural experiment with which to test the durability of social processes in the wake of a significant disaster. In January 2011, Brisbane, the state capital of Queensland, Australia, experienced significant flooding. This was triggered by torrential rainfall across most of the state of Queensland in the days and weeks leading up to the event. Many areas in the Brisbane catchment, like Toowoomba and Lockyer Valley, experienced what some have referred to as inland tsunamis, occurring without warning and killing 23 people (ABC News, 2011). Other areas further downstream had some time to evacuate, though many were unable to undertake activities to preserve homes and belongings in time.

The flood waters peaked on the 13th of January, 2011. In the worst affected areas, few homes or streets escaped inundation and numerous homes were flooded to the roofline. The central business district, as well as local shopping centers and businesses were badly affected in Brisbane and Ipswich (two major cities in the Brisbane Statistical Division). Infrastructure such as the commuter ferry system, major arterial roads, riverside pedestrian facilities and sporting and recreational amenities were lost. Additionally, tens of thousands of residents were without power for several days and many communities were completely inaccessible by road (Wickes et al., 2015).

Media accounts before and after the flood disaster suggested that Brisbane not only maintained a strong sense of neighborhood, but was able to mobilize quickly and efficiently to redress the damage caused by flooding. However, we know that social capital and collective efficacy are unequally distributed across neighborhoods in this city (Mazerolle, Wickes and McBroom, 2010; Wickes, Zahnow, White and Mazerolle, 2013). In some neighborhoods, residents may have banded together and harnessed the necessary resources to respond to the flood. In others, networks may have been weak to start with, limiting the neighborhood's ability respond to the challenges brought about by the flood. Alternatively, the flood itself may have generated neighborhood level shifts in socio-demographics and social functioning that reduced or enhanced neighborhood flood responses.

Using multilevel structural equation modeling, we draw on pre- and post- disaster census and survey data from over 4,000 residents living across 148 communities and examine the extent to which the Brisbane flood had sustained effects on social capital and collective efficacy. Further, we assess the stability of the socio-demographic composition of neighborhoods and how stability or change in these structural characteristics affect neighborhood social processes over time.

Specifically, we ask:

RQ1 How stable are measures of neighborhood socio-demographics preceding and following the flood? Are there differences in flood affected and non-flood affected communities?

RQ2 How stable are measures of neighborhood level collective efficacy and social capital *preceding* the flood?

RQ3 How stable are measures of collective efficacy, social cohesion and trust, and reciprocated exchange in the *post flood* environment and are there differences in flood affected and non-flood affected communities?

RQ4 What is the relationship between neighborhood level socio-demographics and neighborhood level collective efficacy, social cohesion and trust, and reciprocated exchange? Do these relationships vary by flood affected and non-flood affected communities?

3.0 Materials and Methods

3.1 The Australian Community Capacity Study

The data we analyze come from the Australian Community Capacity Study (ACCS), which was designed to complement the Project for Human Development in Chicago Neighborhoods (PHDCN) and other international multilevel studies of urban neighborhoods.

It is a multi-million dollar longitudinal project funded exclusively by the Australian Research Council (ARC) that includes four waves of data collection in Brisbane, one wave of data collection in Melbourne, seven in-depth case studies of Brisbane neighborhoods and an ethnic neighborhood sample of residents from Indian, Vietnamese and Arabic speaking backgrounds in both Brisbane and Melbourne (see http://www.uq.edu.au/accs/index.html).The primary goal of the ACCS is to better understand the spatial and temporal dynamics of neighborhood resilience, crime and disorder. The theoretical underpinnings of social capital, social disorganization and collective efficacy – the primary focus of our paper – are also central to the ACCS.

The current study employs three waves of data collected in 2008, 2010 and 2012 representing the second, third and fourth waves of the ACCS survey conducted in the Brisbane Statistical Division (BSD)[3]. Brisbane is the state capital of Queensland and the third largest city in Australia with a population of approximately 1.9 million people. The ACCS sample comprises 148 randomly drawn neighborhoods[4] with a residential population ranging from 245 to 20,999 (total neighborhoods in the BSD = 429 with a residential population ranging from 15 to 21,001).[5] The ACCS neighborhoods include those that are adjacent to the central business district and those located in peri-urban areas that have experienced significant population growth.

3.2 The ACCS Survey Participants

The participant sample for Waves 2, 3 and 4 includes two distinct groups: the longitudinal sample and the top up sample. In Wave 2, the full sample included 4,324

[3] We focus on waves 2, 3 and 4 of the Brisbane ACCS survey as wave 1 used neighborhood units of analysis that are not comparable to those in the later waves.
[4] In Australia, the term "suburb" is used to refer to a feature that in the U.S. would be referred to as a "neighborhood". Suburbs are similar to census tracts in the U.S. context, though in some cases Brisbane suburbs may be larger than census tracts as they are not determined by population. We use the concept 'neighborhood' throughout this paper.
[5] The ACCS suburbs are randomly selected from the total population of state suburbs and many suburbs in the sample are not contiguous.

respondents comprising 1,077 participants from Wave 1 and a total up sample of 3,247 individuals. The Wave 3 sample included 4,403 participants, of whom 2,248 were included in prior waves and 2,155 were a top-up sample. The Wave 4 sample size included 4,132 respondents of whom 2,473 were longitudinal participants and 1,659 top up participants. Participants were randomly selected using random digit dialing. The consent and completion rate for the ACCS was 52.50 percent for Wave 2, 68.52 percent for Wave 3 and 46.27 percent for Wave 4. This rate represents the number of interviews completed proportional to the number of in-scope contacts. For further information, please see http://www.uq.edu.au/accs/index.html.

The ACCS surveys were conducted by the Institute for Social Science Research at the University of Queensland. Trained interviewers used computer-assisted telephone interviewing to administer the survey. The in-scope survey population included all people aged 18 years or over who were usually resident in private dwellings with telephones in the selected communities[6]. Wave 2 of the ACCS survey was conducted between September 2007 to May 2008 and Wave 3 was conducted between August and December, 2010. Wave 4 of the ACCS survey was conducted from mid-May to mid-August, 2012, approximately 15 months after the Brisbane flood event. This is important since it allows us to examine whether there are sustained (as opposed to immediate, and potentially short-term) changes in neighborhood characteristics and processes following the flood.

Of the 148 communities comprising the ACCS sample, 43 were directly impacted by rising floodwaters (see Figure 1). The socio-economic profile of these areas ranged from very low (AUD727 (approximately USD523) median weekly household income) to very high (AUD2716 (approximately USD1852) median weekly household income). The median

[6] The number of mobile phone only users is significantly lower in Australia compared to the US. In 2008, 90% of the population was covered by landline phones and in 2011 (a period that aligns with the last wave of our sample) the number of mobile phone-only users was estimated at 19% (Australian Communications and Media Authority, 2012).

weekly household income for the flooded neighborhoods did not statistically differ from that of non-flooded neighborhoods (AUD 1584 (approximately USD1080) and AUD1524 (approximately USD1039)), respectively. An independent samples t-test (t=0.0237, df=146, ns) showed the attrition rate was not statistically different in the flooded or non-flooded neighborhoods in the Wave 4 sample. Further, 46 percent (total n=1,915) of Wave 4 ACCS participants reported that they had been impacted by the flood event.

3.3 Administrative Data

In addition to the ACCS survey data, we use data from the Queensland Reconstruction Authority (QRA) to assess flood impact at the neighborhood level. We also use census data from the Australian Bureau of Statistics (ABS) for 2006 and 2011 to examine the impact of socio-demographic variables across the three waves of data, with the 2006 census data being collected just prior to the Wave 2 data (collected in 2007-2008) and the 2011 census data just prior to the Wave 4 data (collected in 2012). In our analyses, we examine a variety of neighborhood socio-structural characteristics, which we describe in further detail below.

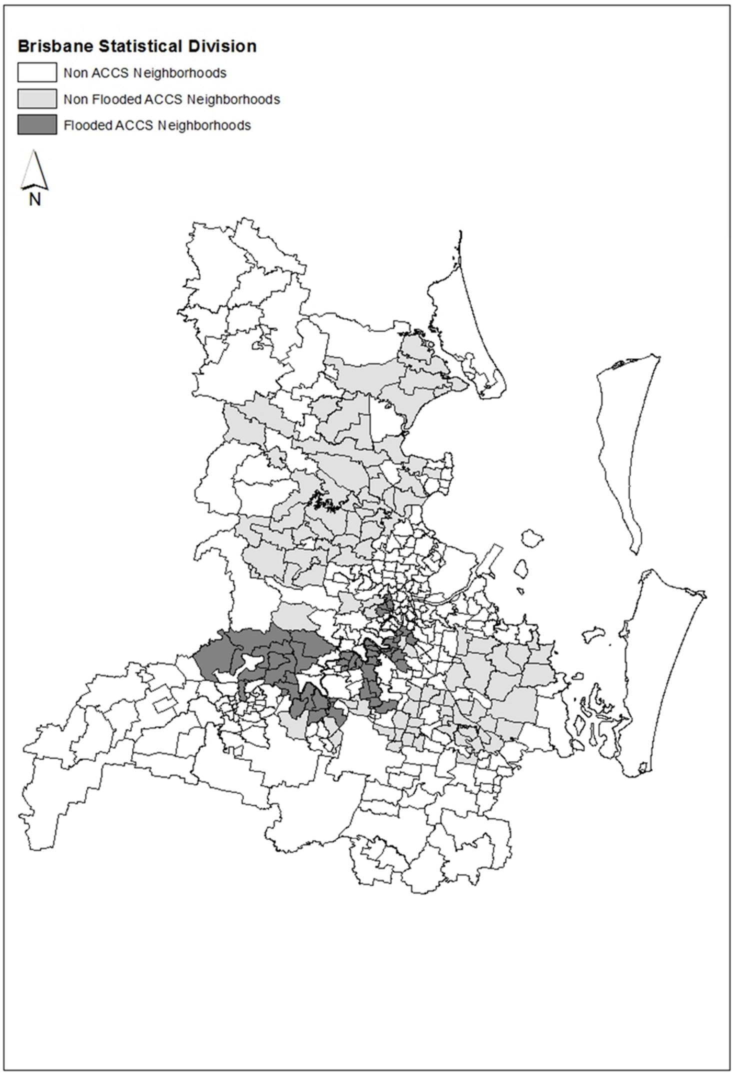


Figure 1. Map of flooded and non-flooded ACCS neighborhoods

3.4 Variable Information

The key goal of this paper is to assess the extent to which the Brisbane Flood Disaster influenced neighborhood social processes in flooded and non-flooded communities. We examine two indicators of social capital: social cohesion and trust, and reciprocated exchange. In addition to our measures of social capital, we examine the durability of collective efficacy in a pre- and post-flood context. We describe these measures and the related social structural context variables we use in our analyses below.

<u>Social Cohesion and Trust:</u> Social cohesion is an important indicator of social capital as it represents a sense of belonging and attachment and symbolizes a working trust of residents

(Markus and Dharmalingam, 2009; Sampson, Morenoff, and Gannon-Rowley, 2002). In our analyses, we use a scale comprising 4 items designed to capture social cohesion and trust. These items are listed in Appendix 1 and the item specific univariate statistics appear in Appendix 2, where we note the overall item mean by year, as well as the item mean by flood status of the community the respondent lived in. The item means for social cohesion and trust do not change much over time or differ much across flood status of the community, with most differences being less than 0.10 units. Our scale is identical to the one used in the PHDCN and represents the norms of trust and reciprocity central to any definition of social capital in the literature (see Coleman, 1988, 1990; Putnam, 2000; Sampson, Raudenbush and Earls, 1997). Approximately 12 percent of the variation in social cohesion and trust is attributable to differences across communities.

<u>Reciprocated Exchange</u>: In our analyses we also assess the durability of social networks. We employ a scale of items that represent ‘activated’ networks derived from the PHDCN (Sampson, 2013; Sampson et al., 1999). The 3 items that comprise this scale assess the frequency with which neighborhood residents provide material and social support to each other (again, see Appendix 1 for items and Appendix 2 for univariate statistics). Similar to social cohesion and trust, the item means for reciprocated exchange tend to be stable over time and to show small differences across flood status of the community. Approximately 5 percent of the variation in this scale is attributable to differences across communities.

<u>Collective Efficacy:</u> In order to capture the willingness of residents to work together to solve local problems and assess the durability of this neighborhood property over time, we use 8 collective efficacy items employed in each wave of the ACCS. Again these items were derived from the PHDCN and are widely used internationally (Mazerolle, Wickes and McBroom, 2010; Sampson, Raudenbush and Earls, 1997). These items are noted in Appendix 1 and the univariate statistics in Appendix 2, and much like the patterns for social cohesion

and trust as well as reciprocated exchange, the item means are stable over time and show small differences across flood status of the community. Approximately 12 percent of the variation in this scale is attributable to differences across communities.

Socio-Structural Variables

In the disaster literature, and the neighborhood effects literature more broadly a number of socio-economic characteristics may influence the durability of neighborhood processes over time - these variables are also used in the creation of disaster vulnerability indices (Cutter et al., 2003; Cutter et al., 2008; Sampson et al., 1997; Sampson et al., 2002).

Concentrated Disadvantage: To capture concentrated disadvantage, we followed the work of Sampson and others (Sampson et al., 1997) and used principal components analysis to create a single factor for both 2006 and 2011 comprised of the following variables from the 2006 and 2011 ABS Census data: percentage of families with one parent, percentage of households classified as low income, percentage of the population classified as Aboriginal or Torres Straight Islanders, and the percentage of the population unemployed.

Ethnic Diversity: To measure the relationship between ethnic diversity and neighborhood processes over time, we include a Blau (1977) index of language diversity from the 2006 and 2011 ABS census data to calculate neighborhood level language diversity[7]. Recognizing that ethnic diversity encompasses more than just language, previous research in the Australian context shows that language diversity is more consequential than ancestral diversity for neighborhood social processes (Benier and Wickes, 2015; Leigh, 2006; Wickes et al., 2013).

[7] To create the language diversity measure we used the regional language categories from the census for the following regions: Northern Europe, Southern Europe, Eastern Europe, South West Central Asia, Southern Asia, South East Asia, Eastern Asia, Australian Indigenous Languages and English only.

Residential Instability: To assess the effect of residential instability on neighborhood social processes, we use the same single item measure from the ABS 2006 and 2011 Census: the percentage of people living at a different address five years ago.

Median Income: To assess the effect of overall neighborhood economic resources, we use the same single item from the ABS 2006 and 2011 Census: median household income.

Flood Impact: We were not able to access a reliable index of flood severity. We therefore used data collected by a government agency charged with overseeing the rebuilding of disaster areas. The Queensland Reconstruction Authority (QRA) provided data that allowed us to identify the neighborhoods that experienced flooding. Neighborhoods in the ACCS sample are coded as 0 if they were not flooded and a 1 if they were flooded.

3.5 Analytic Approach

Our primary interest is in testing whether levels social cohesion and trust, reciprocated exchange, and collective efficacy are similarly stable over time across flooded and non-flooded communities. We also test whether stability or change in these processes is related to the relative stability of neighborhood structural characteristics. While these questions appear simple, testing them requires estimating complex multilevel structural equation models with latent variables. In general, the analytic approach we take to analyzing these data is consistent with standard recommendations and begins by allowing for maximum variability in the unstandardized coefficients across communities (Bollen, 1989). As we explain below, with each successive step, we impose greater restrictions on the estimated model to test for similarities and differences across communities by flood status.

As a first step, we estimated a confirmatory factor analysis (CFA) for our social cohesion and trust, reciprocated exchange and collective efficacy factors that ignored the multilevel nature of the data. We used the same items for Waves 2, 3 and 4 of the ACCS data, so that we had latent factors for all three measures for each of the three waves of data. Our aim for this first step was to establish the consistency of these measures across waves. Although preliminary analyses suggested the data could be modeled as a second-order factor model (i.e., a higher-order single factor would account for the correlation among the three wave-specific factors), this modeling strategy would have precluded a more direct test of the stability and change processes we are interested in testing, since it would involve statistically controlling the longitudinal correlations we want to model[8].

Following the estimation of the CFA, we then added in the multilevel component, which is modeled as another latent variable (Muthén and Muthén, 1998-2015). Consistent with the terminology of other multilevel models, we can think of this latent variable as a random intercept for the latent factors social cohesion and trust, reciprocated exchange and collective efficacy. This gives us an estimate of the amount of variation across neighborhoods – in the multilevel modeling approach, this is our “between” estimate of variance of the latent factors across the neighborhoods included in the ACCS. Following convention, we estimate a single between factor for the latent factor at each of the three waves, instead of three separate between factors that represent between variation in the latent factor at each wave of data (Muthén and Asparouhov, 2015). Muthén and Asparouhov (2015) note that it is common for the between factor in a multilevel CFA to be represented by a smaller number of factors, as is the case here.

With this multilevel factor included, we then split the sample by whether the neighborhood experienced flooding or not, constraining the between factor to be equal across the two sets of communities. This constraint is necessary to enable model convergence, and

[8] We do not report the results from the three CFA models, but these results are available from the authors upon request.

in practice, does not affect the substance of any model we estimate. We then tested for measurement invariance across flooded and non-flooded communities to assess whether social cohesion and trust, reciprocated exchange and collective efficacy operated in the same way across the two sets of neighborhoods. This test for measurement invariance also gets at one of our key questions: How stable are social cohesion and trust, reciprocated exchange and collective efficacy in communities that have experienced external shocks, such as a natural disaster?

Following the test for measurement invariance, we imposed structural constraints on the effects of each factor – social cohesion and trust, reciprocated exchange and collective efficacy – from Wave 2 to Wave 3, and then from Wave 3 to Wave 4. The test of these constraints indicates whether the effect of social processes changes over time or varies by flood status of the neighborhood. To the extent the effects are stable over time, there will be evidence of durability. If the effects increase over time, then it provides evidence of increasing social cohesion, while a decreasing effect would indicate a weakening of social cohesion. In particular, our interest is in what effect the flooding had on these communities' social capital and collective efficacy: did these processes weaken, strengthen, or stay the same? And how does this pattern compare to that for the communities that did not experience any flooding?

We then test whether the overall pattern set of relationships linking social cohesion and trust, reciprocated exchange and collective efficacy over time are affected by neighborhood level structural characteristics. Since the census data were collected in years that did not line up directly with the ACCS data, we modelled the effects of the structural covariates in four different ways: (1) the 2006 census value only, (2) the 2011 census value only, (3) the difference (change) score from 2006 to 2011 (i.e., the 2006 value was subtracted from the 2011 value), and (4) the mean of the 2006 and 2011 values.

The demographic covariates included in our analyses are the means of concentrated disadvantage, residential instability, ethnic diversity, and median income. Each covariate is measured as described above.

For all models we use a full-information maximum likelihood estimator with robust standard errors that uses all available data for each analysis[9]. In addition, all of the models we estimated assume the observed variables – the survey responses for social cohesion and trust, reciprocated exchange and collective efficacy – are continuous. In some of the initial CFA models, we estimated models treating the survey responses as ordinal. The computing time increased significantly at the same time there were no meaningful differences between the models assuming continuous measures and those assuming ordinal measures. Consequently, we report only those results assuming continuous measures.

Summary of Analytic Approach

In light of the relatively complicated series of analyses that we will be presenting below, we want to highlight the key steps in our approach as follows:

1. Estimation of a confirmatory factor analysis (CFA) for the three social process latent variables.
2. Estimation of a confirmatory factor analysis for the three social process latent variables with the addition of the multilevel error component.
3. Split the sample by flood status of the community and test for measurement invariance in the CFAs for the three social process latent variables by flood status.
4. Test for structural effects of the three social process latent variables:

[9] Since data were missing on only about 2 to 4% of item responses, with no systematic pattern of missingness, no special actions were viewed as necessary to impute values for the missing responses.

a. Stability and/or change over time within the same communities.

b. Invariance across communities by flood status.

5. Test for invariance in neighborhood level structural characteristics by flood status.

4.0 Results

4.1 Research Question 1: How stable are measures of neighborhood socio-demographics preceding and following the flood?

Prior to presenting the results for the three social processes that are the primary focus of our paper, we address our first research question by examining the degree of change and stability across the 148 neighborhoods in four key social and demographic characteristics: concentrated disadvantage, residential instability, ethnic diversity, and median income. Panel A of Table 1 presents the means for each of the four characteristics for 2006 and 2011 split by flood status. The last column provides a t-test for difference in the characteristic between flooded and not flooded neighborhoods. In 2006, the two groups of neighborhoods differed little by flood status, with only ethnic diversity showing a statistically significant difference – those neighborhoods that were later flooded had a greater level of ethnic diversity than those neighborhoods not flooded. The differences across neighborhoods were more pronounced in 2011 – the post-flood period. Flooded neighborhoods had fewer new residents and higher levels of ethnic diversity than non-flooded neighborhoods. Important to the natural design element of our study, these results suggest that the two groups of neighborhoods were generally similar to each other prior to the flood, but start to look different from each other after the flood.

Change within neighborhoods is presented in Panel B of Table 1. The far right column again compares neighborhoods that were flooded to those not flooded. Flooded and non-flooded neighborhoods experienced significant change between 2006 and 2011, yet when we compare change within neighborhoods by flood status, we see that flooded neighborhoods showed significantly greater increases over time in residential stability and median income than that observed in non-flooded neighborhoods. This suggests that lower income renters, who were likely renting their property, relocated to other areas with few new people coming into the neighborhood to replace them.

Table 1: Means of Socio-Demographic Characteristics and Changes by Neighborhood Flood Status and Year

Panel A: Means Socio-Demographic Characteristics – Between Neighborhood Differences

2006

Variable	Not Flooded	Flooded	Difference
Residential Instability	-0.053	0.118	-0.171
Concentrated Disadvantage	-0.067	0.148	-0.215
Ethnic Diversity	0.230	0.317	-0.087***
Median Income	1218.539	1238.043	-19.504

2011

Variable	Not Flooded	Flooded	Difference
Residential Instability	-0.152	0.338	-0.491*
Concentrated Disadvantage	-0.053	0.117	-0.170
Ethnic Diversity	0.255	0.339	-0.084**
Median Income	1534.510	1614.761	-8.251

Panel B: Means of Changes in Socio-Demographic Characteristics (2011 – 2006) – Within Neighborhood Differences Comparison

Variable	Not Flooded	Flooded	Difference
Residential Instability	-0.099	0.220*	-0.319**
Concentrated Disadvantage	0.014	-0.031	0.045
Ethnic Diversity	0.025***	0.023**	0.002
Median Income	315.971***	376.717***	-60.747*

*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

The results in Table 1 show that in 2006 (pre-flood period) the two sets of neighborhoods were generally similar on these four key social and demographic characteristics, but show evidence of greater differences in 2011 (post-flood period). All neighborhoods show evidence of change over time, but those neighborhoods that experienced flooding appear to have experienced greater increases compared to those neighborhoods that did not experience flooding.

4.2 How stable are measures of social capital and collective efficacy before and after the flood in flooded and non-flooded neighborhoods?

For each of our two indicators of social capital - social cohesion and trust, reciprocated exchange – and our measure of collective efficacy, we estimate multilevel structural equation models using the process described above to locate the best model to assess how stable or variable each process is across the 148 ACCS neighborhoods. Due to the complexity and variability in the findings, we address each process separately.

<u>Social Cohesion and Trust</u>

We begin by assessing the stability of our measure of social cohesion and trust across flooded and non-flooded neighborhoods – a test for measurement invariance. Here our aim is to establish how similar these processes are across neighborhoods irrespective of flood status. We then examine the stability of social cohesion and trust measures over time within flooded and non-flooded communities to test whether social cohesion and trust is impervious to a sudden and unpredictable exogenous shock. To test for this structural invariance, we estimate the structural equation model with latent variables for social cohesion and trust, starting with a model that only constrained the between level random effect to be the same across the two sets of communities (i.e., the equivalent of the random intercept for the latent variable). We then sequentially introduce constraints on the coefficients to the model that allow for the testing of both measurement invariance and structural invariance. We used the Satorra-Bentler scaled chi-square test to assess whether the additional constraints significantly deteriorated the fit of the model (Satorra-Bentler, 2001). Table 2 presents the model tests in two parts. Panel A presents the model estimated, the value of the log-likelihood function, the correction factor, the number of coefficients estimated, the Root Mean Squared Error of Approximation (RMSEA), and the Tucker Lewis Index (TLI). Panel B presents the test for differences in the nested (and increasingly constrained) models: the scaled Satorra-Bentler chi-square statistic, degrees of freedom, and p-value for that chi-square test. Larger values of the chi-square that appear as statistically significant (i.e., $p < 0.05$) indicate a statistically significant loss of fit to the model, while p-values greater than 0.05 indicate no statistically significant loss of fit as a consequence of increasing constraints imposed on the model.

Table 2: Test of Equality Constraints for Social Cohesion and Trust (SCT) by Neighborhood Flood Status

Panel A: Model Statistics

Model	Coefficients Constrained to Equality across Flood Status	Log-likelihood	Correction Factor	Number of coefficients	RMSEA	TLI
1	Factor Loadings	-60101.798	1.647	64	0.037	0.891
2	Variance of SCT at Wave 2	-60102.77	1.646	63	0.037	0.891
3	Variance of random effect	-60103.003	1.651	62	0.037	0.892
4	Variances of	-60109.074	1.561	50	0.035	.901

	survey items					
5	SCT effects (t-1) on SCT (t)	-60110.963	1.573	48	0.035	0.902
6	All SCT effects	-60111.613	1.587	47	0.035	0.902
7	Effects of demographic covariates	-60114.916	1.652	43	0.035	0.903

Panel B: Model Comparisons

Models Compared	Chi-square	Df	P
1 v. 2	1.137	1	0.286
2 v. 3	0.349	1	0.555
3 v. 4	5.993	12	0.916
4 v. 5	2.968	2	0.227
5 v. 6	1.421	1	0.233
6 v. 7	7.437	4	0.115

The results in Panel B of Table 2 show that none of the additional coefficient constraints negatively affect the fit of the model – none of the chi-square tests are statistically significant. This set of findings suggests that we have both measurement and structural invariance across the two groups of neighborhoods. The unstandardized coefficient estimates from Model 7 appear in Figure 2 – since they are identical across the two groups of neighborhoods, only one path diagram is shown. Appendix 3, Panel A, contains all of the coefficient estimates for Model 7, including the estimates of the random variation across communities (i.e., the "Between Level" estimates for each measurement model).

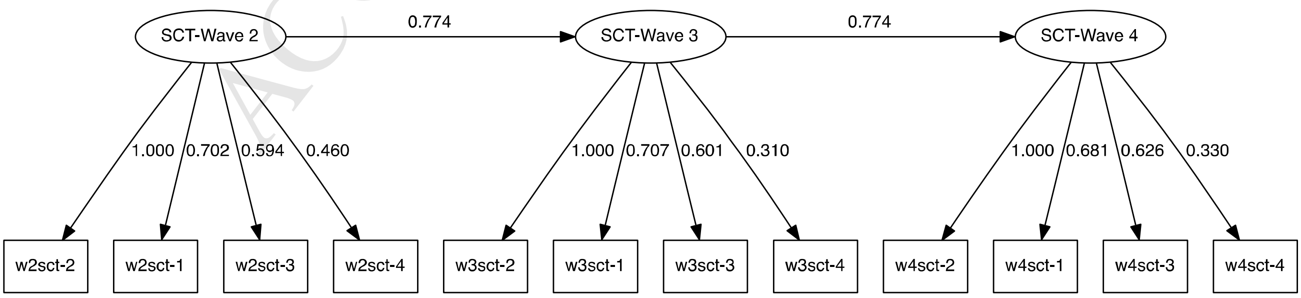


Figure 2: Social Cohesion and Trust

The evidence in support of measurement invariance bolsters our confidence in the measurement of social cohesion and trust as this measure does not vary by neighborhood flood status. Had there been evidence of variance in the measurement model, it would have raised questions about the generality of the items used to assess this process and implied that the construct itself is sensitive to flood status—in other words, that social cohesion and trust actually means something different to individuals in flooded compared to non-flooded communities. This, however, does not appear to be the case. We find that of the four items used to measure social cohesion and trust, the items asking about whether the neighborhood was close-knit, would be willing to help each other, and trusted each other all had similar strong relationships with the social cohesion and trust latent variable, while the item that asked about a lack of similar values (a negatively worded item, while the others were all positive) had a much weaker relationship with the social cohesion and trust latent variable. This pattern is consistent across waves of data providing further support for the use of these items to measure social cohesion and trust.

Having established measurement invariance across the two sets of neighborhoods, the evidence of structural invariance in the effects of social cohesion and trust from one wave to the next allows us to answer our Research Questions 2 and 3. In the pre-flood period (Waves 2 and 3), we might expect the effect to be stable, but for the effect to change following the flood (Wave 4). Our results suggest a very strong positive relationship over time that is statistically indistinguishable by flood status of the neighborhood (coefficient = 0.774). Regardless of whether we look at the effect of social cohesion and trust at Wave 2 on Wave 3 or the effect from Wave 3 on Wave 4, it is the same value over time and across neighborhood flood status. Our results show a high degree of stability in the effect of social cohesion and trust over time that suggests this process is a resilient characteristic of communities and that a natural disaster – an external "shock" to neighborhood social processes – does not harm neighborhood-level cohesion and trust.

Reciprocated Exchange

To test for change and stability in reciprocated exchange we use an identical process of testing for measurement and structural invariance over time and across the flood status of the ACCS neighborhoods. The tests for measurement and structural invariance in reciprocated exchange appear in Table 3, Panels A and B. There is again evidence for strong measurement invariance – the factor loadings and variances are equal across two groups of neighborhoods. There are two model comparisons that are borderline ambiguous. The first of these appears when the variances for all of the individual items are constrained to be equal across flood status (Model 3 v. 4, p=0.088). The second appears when the effects of reciprocated exchange are held constant across flood status (Model 4 v. Model 5, p=0.057). The other model indices do not change much at all, suggesting there was no major negative impact on the overall fit of the model.

Table 3: Test of Equality Constraints for Reciprocated Exchange (RE) by Neighborhood Flood Status

Panel A: Model Statistics

Model	Coefficients Constrained to Equality across Flood Status	Log-likelihood	Correction Factor	Number of coefficients	RMSEA	TLI
1	Factor Loadings	-45631.497	1.204	52	0.034	0.942
2	Variance of RE at Wave 2	-45632.403	1.206	51	0.033	0.943
3	Variance of random effect	-45634.057	1.194	50	0.033	0.943
4	Variances of survey items	-45643.505	1.182	41	0.032	0.946
5	RE effects (t-1) on RE (t)	-45646.957	1.180	39	0.032	0.947
6	All RE effects	-45648.126	1.176	38	0.032	0.947
7	Effects of demographic	-45652.716	1.220	34	0.032	0.948

	covariates					

Panel B: Model Comparisons

Models Compared	Chi-square	df	p
1 v. 2	1.644	1	0.200
2 v. 3	1.832	1	0.176
3 v. 4	15.133	9	0.087
4 v. 5	5.654	2	0.059
4 v. 6	7.347	3	0.061
5 v. 6	1.755	1	0.185
6 v. 7	11.446	4	0.022*

*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

The unstandardized effects from Model 6[10] are displayed in Figure 3[11]. Again, since all of the coefficients have been constrained to be equal across flood status of neighborhoods, there is only one figure. Similar to the pattern of results we observed with social cohesion and trust, reciprocated exchange has a strong positive effect that is the same over time and across flood status (coefficient = 0.815). In light of our Research Questions 2 and 3 that focus on change and stability of neighborhood social processes pre- and post-flood, we find a pattern of stability in the effect of reciprocated exchange that holds over time and across flood status of the neighborhoods. Once again, the evidence suggests that an external shock in the form of a natural disaster does not appear to negatively affect reciprocated exchange among residents.

[10] We discuss the difference between Models 6 and 7 below, explaining that the demographic covariates cannot be constrained across communities.
[11] The full set of coefficient estimates, including the estimates of random variation across community, appear in Appendix 3, Panel B.

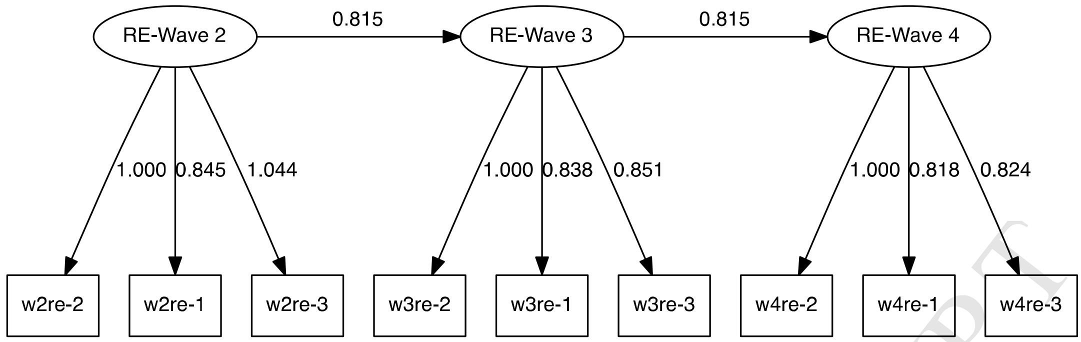


Figure 3: Reciprocated Exchange

Collective Efficacy

Our test for change and stability of collective efficacy over time follows the same analytical strategy. Table 4, Panels A and B, parallel those in Tables 2 and 3, where Panel A presents the model fit statistics[12] and Panel B presents the tests for differences in nested models. As we found in the analyses of social cohesion and trust and reciprocated exchange, there is again evidence of strong measurement invariance (Models 1 through 4), indicating that the items used to assess collective efficacy are consistent across neighborhoods, regardless of flood status. As we have claimed above, the measurement invariance helps to assure us that we are, in fact, assessing the same process in the different neighborhoods and that collective efficacy does not mean something different in neighborhoods that vary by whether or not the neighborhood experienced flooding.

The results for collective efficacy depart from those for social cohesion and trust as well as reciprocated exchange in the test for structural invariance. We find evidence that the effect of collective efficacy varies by flood status of the neighborhood (Model 4 v. Model 5: chi-square=6.701, df=2, p = 0.035) and over time (Model 4 v. Model 6: chi-square=8.664, df=3, p = 0.034).

[12] We note that the value of the TLI is slightly lower for the collective efficacy models, but this is not entirely unexpected, since there were twice as many items included in the analysis and the value of the TLI is sensitive to the number of items included in a model and penalizes models with larger numbers of items (Bentler, 1990).

Table 4: Test of Equality Constraints for Collective Efficacy (CE) by Neighborhood Flood Status

Panel A: Model Statistics

Model	Coefficients Constrained to Equality across Flood Status	Log-likelihood	Correction Factor	Number of coefficients	RMSEA	TLI
1	Factor Loadings	-145505.533	1.358	112	0.037	0.780
2	Variance of CE at Wave 2	-145505.738	1.356	111	0.037	0.780
3	Variance of random effect	-145507.06	1.355	110	0.037	0.781
4	Variances of survey items	-145527.612	1.331	86	0.037	0.788
5	CE effects (t-1) on CE (t)	-145532.122	1.331	84	0.037	0.788
6	All CE effects	-145532.671	1.337	83	0.037	0.788
7	Effects of demographic covariates	-145532.378	1.355	82	0.037	0.788

Panel B: Model Comparisons

Models Compared	Chi-square	df	p
1 v. 2	0.259	1	0.610
2 v. 3	1.804	1	0.179
3 v. 4	28.525	24	0.239
4 v. 5	6.777	2	0.034*
4 v. 6	8.685	3	0.034*
4 v. 7	11.361	4	0.023*

*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

Figure 3 presents the unstandardized coefficients for the effects of collective efficacy from one wave to the next by flood status of the neighborhood based on Model 4[13]. The effect of collective efficacy from one wave to the next is both larger and more stable in the communities that experienced the flood than it is in the communities that did not experience any flooding. For example, the effect of collective efficacy at wave 2 on collective efficacy at wave 3 is 0.844 for the communities that experienced flooding, compared to 0.730 for those

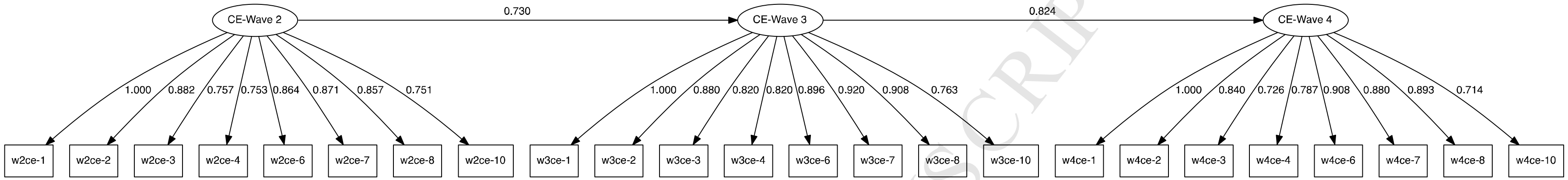
[13] The full set of coefficient estimates, including the estimates of random variation across community, appear in Appendix 3, Panel C.

communities that did not experience flooding. The effect for wave 3 on wave 4 increased slightly in both communities – to 0.854 in those neighborhoods that had been flooded and to 0.824 for those neighborhoods that had not been flooded. Similar to our observations on the other two neighborhood social processes, these results are suggestive of a high level of resilience that only increased following the flood. Interesting, too, is the apparent increase in the effect of collective efficacy over time in both groups, hinting at the possibility that community-based responses to the flooding helped to enhance existing levels of collective efficacy.

4.3 Research Question 4: What are the effects of socio-demographic characteristics on social capital and collective efficacy over time and by flooded and non-flooded neighborhoods?

Concentrated disadvantage, residential instability, ethnic diversity, and median income have the same effect on social cohesion and trust, regardless of whether the neighborhood was flooded or not (Model 6 v. Model 7: chi-square = 7.437, df=4, p=0.115). Figure 5 presents the unstandardized coefficients from the multilevel structural equation model that illustrates the effects of the socio-demographic covariates on social cohesion and trust. All of the specific effects are statistically significant and consistent with prior research, showing that increased levels of concentrated disadvantage (-0.079), residential instability (-0.018), and ethnic diversity (-0.129) are associated with lower levels of social cohesion and trust across neighborhoods. Conversely, higher levels of median incomes (0.030) are associated with increased levels of social cohesion and trust.

Panel A: Not Flooded



Panel B: Flooded

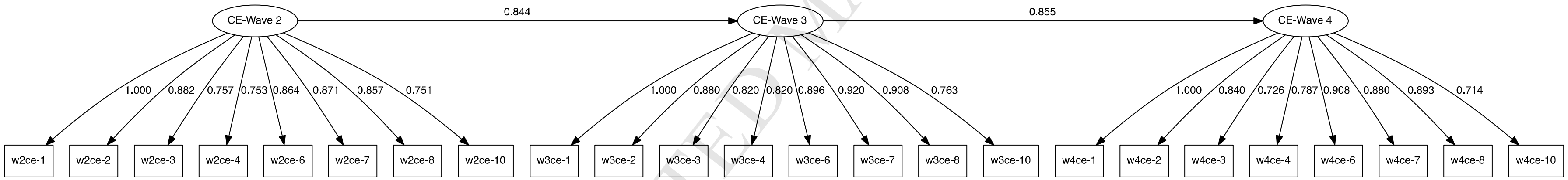


Figure 4: Collective Efficacy

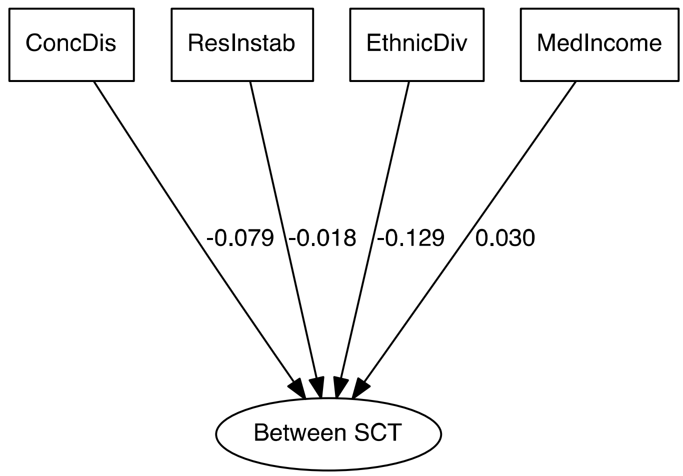


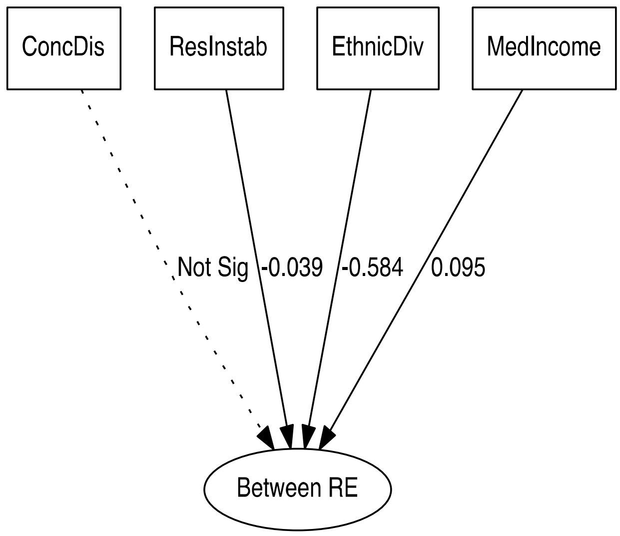
Figure 5: Effects of Socio-Demographic Characteristics on Social Cohesion and Trust

For reciprocated exchange, the socio-demographic characteristics could not be constrained across the flood status of neighborhoods (Model 6 v. Model 7: chi-square = 11.446, df=4, p=0.022), suggesting the effects of these social structural characteristics differed by flood status of the neighborhood. Figure 6 presents the unstandardized coefficients for the effects of the socio-demographic characteristics on reciprocated exchange for neighborhoods not flooded (Panel A) and for neighborhoods flooded (Panel B). Ethnic diversity has a negative effect on reciprocated exchange regardless of flood status, but the magnitude of the effect is greater in those neighborhoods not flooded (-0.584) compared to those neighborhoods that were flooded (-0.364). Median income had positive effects in both sets of neighborhoods, but again with the greater effect in those neighborhoods not flooded (0.095) compared to those neighborhoods that were flooded (0.077). Residential instability had a negative effect (-0.039) in those neighborhoods not flooded, but no effect in neighborhoods experiencing the flood. Concentrated disadvantage does not have statistically significant effect on reciprocated exchange in either the flooded or not flooded neighborhoods.

The results for collective efficacy are similar to those for reciprocated exchange – the socio-demographic characteristics of the neighborhoods could not be constrained to be the same across flood status (Model 4 v. Model 7: chi-square=11.361, df=4, p = 0.023). The unstandardized effects of the socio-demographic characteristics appear in Figure 7 for those neighborhoods not flooded (Panel A) and those flooded (Panel B). Increased levels of concentrated disadvantage were associated with lower levels of collective efficacy, but again, the magnitude of the effect was greater in the neighborhoods not flooded (-0.137) when compared to those flooded (-0.092). Higher levels of ethnic diversity were associated with lower levels of collective efficacy, but the magnitude of the effect was greater in those neighborhoods flooded (-0.808) compared to those not flooded (-0.611). Higher levels of median incomes are associated with increased levels of collective efficacy in both flooded (0.188) and not flooded (0.104) communities. Residential instability does not affect level of collective efficacy in either group of neighborhoods.

Finally, we note that the inclusion of the neighborhood socio-demographic characteristics does not statistically explain the different patterns of effects of collective efficacy over time and by flood status of the neighborhood. In light of the many other demographic covariates that could possibly explain the differences in the effects, and as a check on the robustness of our statistical models, we estimated a series of other models that included a wide range of additional demographic covariates, such as age composition, alternative measures of race-ethnicity, residential stability (owners, renters, etc.), and economic indicators. In no case did the inclusion of one or more of these additional measures help to statistically explain the differences across communities – virtually none of the additional demographic covariates were statistically significant if added to a model that already included the four measures displayed in Figure 7.

Panel A: Not Flooded



Panel B: Flooded

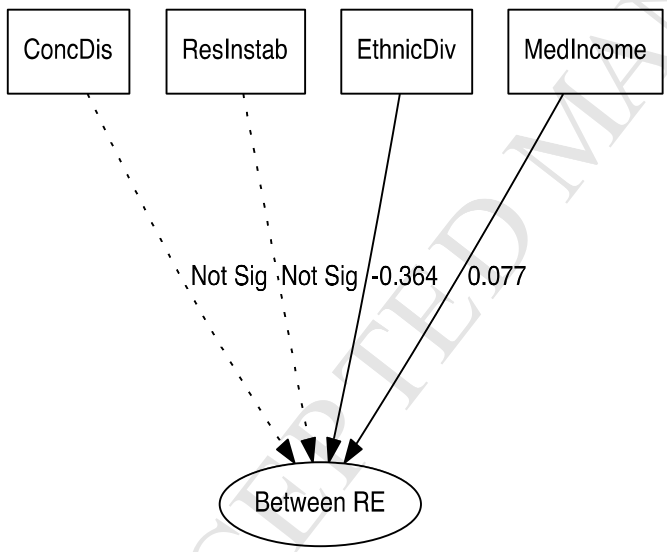
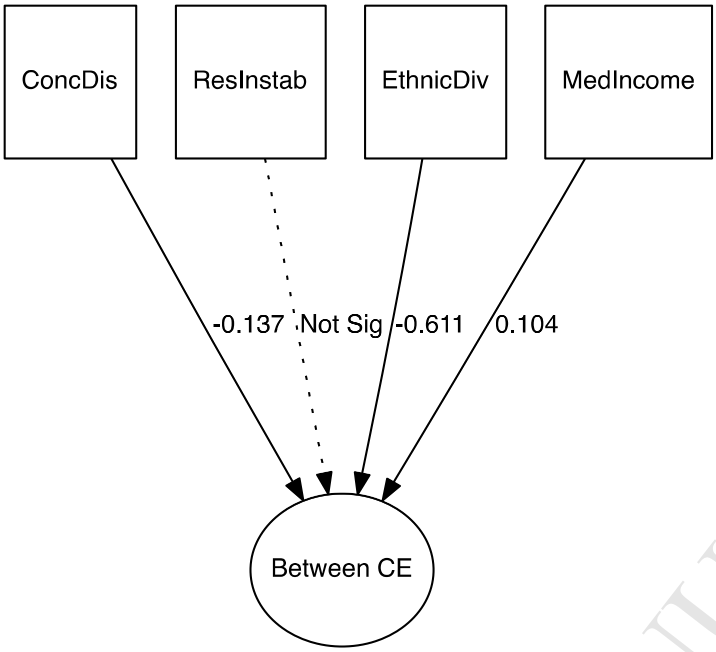


Figure 6: Effects of Socio-Demographic Characteristics on Reciprocated Exchange

Panel A: Not Flooded



Panel B: Flooded

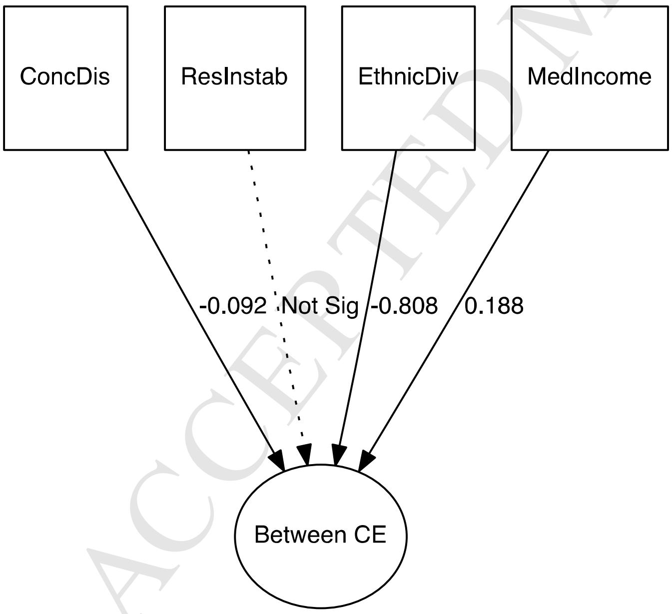


Figure 7: Effects of Socio-Demographic Characteristics on Collective Efficacy

5.0 Discussion

The overarching aim of this research was to better understand the influence of a disaster on the social processes associated with community resilience. Specifically, we wanted to know if neighborhood social capital and collective efficacy could endure a significant exogenous shock. To do this we utilized a novel data set to explore stability and change in social capital and collective efficacy before and after a significant flooding event in Brisbane, Australia. We considered the stability of neighborhood level collective efficacy and social capital preceding and following the flood, and whether stability and/or change differed in flooded areas compared to non-flooded areas. We also assessed the relationship between neighborhood level socio-demographics, collective efficacy and social capital before and after the flood and whether these relationships varied across flooded and non-flooded neighborhoods.

Our paper makes three significant contributions. First we find that three different measures of social capital and collective efficacy commonly used in the sociological literature display significant measurement invariance across flooded and non-flooded communities. Despite calling for a greater focus on the ecometric rigor of neighborhood assessments (Sampson and Raudenbush, 2004), the ecometric properties of neighborhood constructs has received limited attention. Our findings provide strong evidence that the measurement of social cohesion and trust, reciprocated exchange and collective efficacy are virtually indistinguishable across flooded and non-flooded neighborhoods in the ACCS sample and for each wave of the ACCS survey.

Related to this, but perhaps more importantly, our results also indicate that our neighborhood measures demonstrate remarkable stability across time, in flooded and non-flooded neighborhoods. This is especially true for social cohesion and trust, which remained virtually unchanged. Yet there were interesting differences in the *effect* of these measures across time, particularly for collective efficacy. Although levels of collective efficacy increased across the sample between waves 3 and 4, it demonstrated greater stability over time in flooded neighborhoods compared to non-flooded ones. Further, collective efficacy after the flood event was slightly stronger in flooded neighborhoods when compared to non-flooded neighborhoods.

Collective efficacy is a situated neighborhood process that relates to “specific tasks such as maintaining public order” (Morenoff et al., 2001, p. 521). Collective efficacy is not necessarily a product of neighborhood networks, nor is it a key element of a neighborhood’s culture - people from diverse backgrounds, with weak social ties, who live in poor neighborhoods can and do agree on important collective norms (Sampson, 1999). Instead, it represents that capacity of a community to respond to task specific issues. When there is no need to respond collectively, collective efficacy lies dormant. For many neighborhoods, there are few opportunities to ‘see’ collective efficacy in action. Although even collectively efficacious communities experience challenges across time, for the most part, collective efficacy is assumed from what residents expect others would do in a crisis. In a case study of collective efficacy, Wickes (2010) found that residents in collectively efficacious communities had limited experience of neighbors working together to solve local problems, but residents knew there was substantial human and economic capital in the neighborhood. From that, they assumed that residents could competently handle problems when and if they arose.

This assumption was tested with the Brisbane flood disaster. We argue that the flood provided an opportunity for residents to gain first-hand knowledge of what others would do in times of a crisis. In the lead-up and the recovery period of the flood event, residents’ actions were highly visible. Thus residents could verify and update their assumptions about the collective capacity of the neighborhood. In return, this could enhance perceptions of collective efficacy. Not only could individuals evaluate collective efficacy in their own communities, but also as it played out across the city's landscape. The Brisbane flood was a heavily televised event. All networks covered the days leading up to the flood, the flood event and the clean-up. Key agencies across Brisbane took to Facebook and Twitter to provide updates to followers. Radio stations reported unfolding events and providing advice on the location of shelters and where residents could go for help. The coverage of the Brisbane flood was, for the most part, positive. An evaluation of flood-related media revealed a focus on community resilience, community spirit and the importance of sharing experiences and providing support to others in the days and weeks following the flood event (Bohensky and Leitch, 2014). Thus the city, in its time of crisis, was framed as collectively efficacious. This, at least in part, explains why collective efficacy increased in both flooded and non-flooded neighborhoods.

Our third contribution sheds important light on the longitudinal relationship between neighborhood socio-demographic structure and neighborhood process. In 2006, the flooded and non-flooded neighborhoods comprising the ACCS sample were similar in terms of median income, residential stability and concentrated disadvantage. Yet in the post flood period, flooded neighborhoods had fewer new residents and higher levels of ethnic diversity than non-flooded neighborhoods. Not surprisingly, there were also within neighborhood changes: flooded neighborhoods showed significantly greater increases over time in residential stability and median income than what was observed in non-flooded neighborhoods. These changes had differential effects on neighborhood processes in flooded and non-flooded areas, particularly for reciprocated exchange. Ethnic diversity and residential instability, for example, negatively influenced reciprocated exchange over time across the sample, but the magnitude of these effects was greater in non-flooded neighborhoods. As other scholars note, renters, minority residents and low incomes residents are likely to relocate after a disaster period (Cutter et al., 2003; Peacock, Dash and Zhang, 2006). In our study we find that non-flooded neighborhoods received more new residents, and more residents speaking a language other than English than flooded areas. In flooded neighborhoods, the median income increased. This suggests a loss of more economically vulnerable residents to other areas. We know that the presence of minority group members and poverty has an influence on social capital in times of disaster quiescence (Sampson, Raudenbush and Earls, 1997; Wickes et al., 2013), our findings suggest that this effect becomes magnified in areas with many newcomers in a post-disaster context.

Our research sheds important light on the resilience of neighborhood processes, yet it is not without limitations. Pre- and post-flood data allow us to examine how neighborhood processes change over time, but we are limited to only three observation points that may or may not represent the true causal process (Taylor, 2015). Unlike developmental trajectories for individuals, it is nearly impossible to effectively track neighborhoods from birth across the life course. Even longitudinal research provides a mere snapshot into the life of a neighborhood. As Sampson (2012, p. 369) argues, social processes are "shaped by context, history and prior expectations" thus they can be both "simultaneously an outcome itself and a potential causal force." As such, we make no claims regarding causality in this paper. The second limitation relates to our unit of analysis. A growing body of research focuses on street segments (Groff, Weisburd and Yang, 2010), the ACCS employs a unit of analysis more akin to those in the PHDCN. As some specific areas *within* a neighborhood likely experienced greater levels of inundation and consequently more damage than others, differences at the micro level of analysis are possible, but these data would not detect them. Finally, the stability we find pre and post flood may also be a factor of the type of disaster we are examining. Natural disasters are more likely to bring about altruistic behaviors, whereas human made disasters lead to what some scholars refer to as corrosive communities (see

Freudenburg, 1997; Freudenburg and Jones, 1991; Gill, Picou and Richie, 2012; Richie, 2004; Richie and Gill, 2010). While social cohesion, reciprocated exchange and collective efficacy demonstrated significant resilience after the Brisbane flood, they may be less able to withstand a disaster that results from government or industry negligence. Drawing on a significant body of research following the Exxon Valdez oil spill (Gill, Picou and Richie, 2012; Ritchie, 2004; Richie and Gill, 2010), it is entirely possible that had Brisbane experienced a disaster owing to human error, our findings may be very different. Thus we do not assume that the ability to withstand one of type of disaster would be true of others.

In summary, our research suggests that the social processes most strongly associated with the concentration of neighborhood social problems are not only ecometrically robust in terms of their measurement, but they show a high degree of stability across time, even in the face of a disaster. We argue that in Brisbane where governments were responsive and media reporting remained focused on community resilience and spirit, the flood provided residents with an opportunity to update their view on the capacity of their neighborhood. Moreover, we find that the changes in the structural features of the neighborhood influence the effect of these social processes longitudinally. In areas that experience greater affluence, stability and ethnic homogeneity over time, these processes strengthen. Conversely, neighborhoods in economic decline demonstrate weakening over time, especially for measures of social cohesion and trust and collective efficacy. But these relationships are uneven across flooded and non-flooded neighborhoods with non-flooded areas perhaps at greater risk for social fracture. This leads us to argue that disaster policy and preparedness initiatives must consider ways to strengthen neighborhood processes in disaster quiescence. However, we also stress the importance of preparing non-disaster affected areas with strategies to effectively and swiftly incorporate new residents in order to avoid the erosion of social capital and collective efficacy in the post-disaster context.

6.0 References

ABC News. 2011. "Toowoomba Swamped by Deadly 'Inland Tsunami." *ABC News*. Retrieved from http://www.abc.net.au/news/2011-01-11/toowoomba-swamped-by-deadly-inland-tsunami/1900720.

Aldrich, D. P. (2012). *Building resilience: Social capital in post-disaster recovery*. Chicago: University of Chicago Press.

Australian Communications and Media Authority (2012). *Communications Report 2011–12*. Canberra: ACMA.

Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. (1997). Self-efficacy: The exercise of control. New York: Freeman.

Barrera Jr, M. (1986). Distinctions between social support concepts, measures, and models. *American Journal of Community Psychology,* 14(4), 413-445.

Barton, A. (1970). *Communities in disaster*. New York: Anchor Press.

Beck, U. (1992). *The risk society.* London: Sage.

Benier, K., and Wickes, R. (2015). The effect of ethnic diversity on collective efficacy in Australia. *Journal of Sociology*. Online first – doi 10.1177/1440783315599595

Benight, C. (2004). Collective efficacy following a series of natural disasters. *Anxiety, Stress and Coping,* 17(4), 401-420.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, 107(2), 238-46.

Bin, O., and Polasky, S. (2004). Effects of flood hazards on property values: evidence before and after Hurricane Floyd. *Land Economics,* 80(4), 490-500.

Blau, P. M. (1977). *Inequality and heterogeneity: A primitive theory of social structure* (Vol. 7). New York: Free Press.

Bohensky, E. L., & Leitch, A. M. (2014). Framing the flood: a media analysis of themes of resilience in the 2011 Brisbane flood. *Regional Environmental Change*, 14(2), 475-488.

Bollen, K. (1989). *Structural Equations with Latent Variables*. New York: Wiley.

Breton, M. (2001). Neighborhood resiliency. *Journal of Community Practice,* 9(1), 21-36.

Brooks-Gunn, J., Duncan, G. J., Klebanov, P. K., and Sealand, N. (1993). Do neighborhoods influence child and adolescent development? *American Journal of Sociology*, 99(2), 353-395.

Browning, C. R., and Cagney, K. A. (2002). Neighborhood structural disadvantage, collective efficacy, and self-rated physical health in an urban setting. *Journal of Health and Social Behavior*, 43(4), 383-399.

Browning, C. R., Wallace, D., Feinberg, S. L., and Cagney, K. A. (2006). Neighborhood social processes, physical conditions, and disaster-related mortality: the case of the 1995 Chicago heat wave. *American Sociological Review*, 71(4), 661-678.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94, S95-S120.

Coleman, J. (1990). Foundations of Social Theory. Cambridge: Harvard University Press.

Cope, M.R., Slack, T., Blanchard, T.C. and Lee, M.R. (2013). Does Time Heal All Wounds? Community Attachment, Natural Resource Employment, and Health Impacts in the Wake of the BP Deepwater Horizon Disaster. *Social Science Research* 42:872-881.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., and Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global Environmental Change*, 18(4), 598-606.

Cutter, S. L., Boruff, B. J., and Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly*, 84(2), 242-261.

Cutter, S. L., Burton, C. G., and Emrich, C. T. (2010). Disaster resilience indicators for benchmarking baseline conditions. *Journal of Homeland Security and Emergency Management*, 7(1), 1-21.

Diez-Roux, A. V., Nieto, F. J., Muntaner, C., Tyroler, H. A., Comstock, G. W., Shahar, E., ... and Szklo, M. (1997). Neighborhood environments and coronary heart disease: a multilevel analysis. *American Journal of Epidemiology*, 146(1), 48-63.

Drukker, M., Kaplan, C., Feron, F., and Van Os, J. (2003). Children's health-related quality of life, neighborhood socio-economic deprivation and social capital. A contextual analysis. *Social Science and Medicine*, 57(5), 825-841.

Elliott, J. R., and Pais, J. (2006). Race, class, and Hurricane Katrina: Social differences in human responses to disaster. *Social Science Research*, 35(2), 295-321.

Erikson, K. T. (1976). *Everything in its path*. New York; Simon and Schuster.

Fay-Ramirez, S., Antrobus, E., & Piquero, A. R. (2015). Assessing the effect of the Queensland "Summer of Disasters" on perceptions of collective efficacy. Social science research, 54, 21-35.

Fong, E., and Chang, L. Y. (2011). Community under stress: Trust, reciprocity, and community collective efficacy during SARS outbreak. *Journal of Community Health,* 36(5), 797-810.

Freudenburg, W.R. (1997). Contamination, corrosion and the social order: an overview. *Current Sociology*, 45 (3), 19–39.

Freudenburg, W.R., and Jones, R.E. (1991). Criminal Behavior and Rapid Community Growth: Examining the Evidence. *Rural Sociology*, 56 (4), 619-645.

Fritz, C. (1968). Disasters. In *International Encyclopedia of the Social Sciences.* New York: The Macmillian Company and Free Press.

Gill, D. A., Picou, J. S., & Ritchie, L. A. (2012). The Exxon Valdez and BP oil spills: A comparison of initial social and psychological impacts. *American Behavioral Scientist*, 56(1), 3-23.

Goltz, J. D., Russell, L. A., and Bourque, L. B. (1992). Initial behavioral response to a rapid onset disaster: a case study of the October 1, 1987, Whittier Narrows earthquake. *International Journal of Mass Emergencies and Disasters* 10(1), 43-69.

Gotham, K. F., & Greenberg, M. (2014). *Crisis cities: disaster and redevelopment in New York and New Orleans*. Oxford University Press.

Groff, E.R., D. Weisburd, and Yang, S-M. (2010). Is it Important to Examine Crime Trends at a Local "Micro" Level?: A Longitudinal Analysis of Block to Block Variability in Crime Trajectories. *Journal of Quantitative Criminology*, 26, 7-32.

Hawdon, J., Ryan, J., and Agnich, L. (2010). Crime as a Source of Solidarity: A Research Note Testing Durkheim's Assertion. *Deviant Behavior*, 31(8), 679-703.

Hawkins, R. L., and Maurer, K. (2010). Bonding, bridging and linking: How social capital operated in New Orleans following Hurricane Katrina. *British Journal of Social Work,* 40(6), 1777-1793.

Hendryx, M. S., and Ahern, M. M. (2001). Access to mental health services and health sector social capital. *Administration and Policy in Mental Health and Mental Health Services Research,* 28(3), 205-218.

Huppert, H. E., and Sparks, R. S. J. (2006). Extreme natural hazards: population growth, globalization and environmental change. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences,* 364(1845), 1875-1888.

Hurlbert, J. S., Beggs, J. J., and Haines, V. A. (2001). Social networks and social capital in extreme environments. In N. Lin, K. Cook, R. S. Burt (eds) *Social capital: Theory and Research* (pp. 209-231). New Brunswick, NJ: Transaction Publishers.

Israel, G. D., Beaulieu, L. J., and Hartless, G. (2001). The Influence of Family and Community Social Capital on Educational Achievement. *Rural Sociology,* 66(1), 43-68.

James, T.F. and Wenger, D.E. (1980). Public Perceptions of Disaster-related Behaviors, In Baker, E. (Ed.) Hurricanes and Coastal Storms. Tallahassee, FL: Florida State University Press.

Johnson, N. R., Feinberg, W. E., and Johnston, D. M. (1994). Microstructure and panic: The impact of social bonds on individual action in collective flight from the Beverly Hills Supper Club fire. In R.R. Dynes & K.J. Tierney (Eds.) *Disasters, Collective Behavior and Social Organization* (pp. 168-189) Newark: University of Delaware Press.

Kawachi, I., Kennedy, B. P., Lochner, K., and Prothrow-Stith, D. (1997). Social capital, income inequality, and mortality. *American Journal of Public Health,* 87(9), 1491-1498.

Kim, Y. C., and Kang, J. (2010). Communication, neighbourhood belonging and household hurricane preparedness. *Disasters,* 34(2), 470-488.

Kimhi, S., and Shamai, M. (2004). Community resilience and the impact of stress: Adult response to Israel's withdrawal from Lebanon. *Journal of Community Psychology,* 32(4), 439-451.

Kirschenbaum, A. (2004). Generic sources of disaster communities: a social network approach. *International Journal of Sociology and Social Policy*, 24(10/11), 94-129.

Kreps, G. A. (1984). Sociological Inquiry and Disaster Research. *Annual Review of Sociology* 10:309–30.

Krivo, L. J., and Peterson, R. D. (2000). The structural context of homicide: Accounting for racial differences in process. *American Sociological Review,* 65(4), 547-559.

LaLone, M. B. (2012). Neighbors helping neighbors an examination of the social capital mobilization process for community resilience to environmental disasters. *Journal of Applied Social Science,* 6(2), 209-237.

Leigh, A. (2006). Trust, inequality and ethnic heterogeneity. *Economic Record*, 82(258), 268-280.

Lindell, M. K., Tierney, K. J., and Perry, R. W. (2001). *Facing the Unexpected: Disaster Preparedness and Response in the United States*. Washington DC; Joseph Henry Press.

Lochner, K. A., Kawachi, I., Brennan, R. T., and Buka, S. L. (2003). Social capital and neighborhood mortality rates in Chicago. *Social Science and Medicine*, 56(8), 1797-1805.

Magis, K. (2010). Community resilience: an indicator of social sustainability. *Society and Natural Resources,* 23(5), 401-416.

Markowitz, F. E., Bellair, P. E., Liska, A. E., and Liu, J. (2001). Extending social disorganization theory: Modeling the relationships between cohesion, disorder, and fear. *Criminology,* 39(2), 293.

Markus, A., and A. Dharmalingam. (2009). *Mapping Social Cohesion: The 2007 Scanlon Foundation Surveys*. Victoria: Monash Institute for the Study of Global Movements.

Massey, D.S., Gross A.B. and Shibuya, K. (1994). Migration, Segregation, and the Geographic Concentration of Poverty. *American Sociological Review,* 59(3), 425-445.

Mazerolle, L., Wickes, R., and McBroom, J. (2010). Community variations in violence: The role of social ties and collective efficacy in comparative context. *Journal of Research in Crime and Delinquency,* 47(1), 3-30.

Morenoff, J. D., Sampson, R. J., & Raudenbush, S. W. (2001). Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology*, 39(3), 517-558.

Mullins, A., and Soetanto, R. (2013). Ethnic differences in perceptions of social responsibility: Informing risk communication strategies for enhancing community resilience to flooding. *Disaster Prevention and Management: An International Journal,* 22(2), 119-131.

Murphy, B. L. (2007). Locating social capital in resilient community-level emergency management. *Natural Hazards*, 41(2), 297-315.

Muthén, B., and Asparouhov, T. (2015). Causal effects in mediation modeling: An introduction with applications to latent variables. *Structural Equation Modeling: A Multidisciplinary Journal,* 22(1), 12-23.

Muthén, L. K. and Muthén, B. O. (1998-2015). *Mplus User's Guide: Seventh Edition*. Los Angeles, CA: Muthén and Muthén.

Nilson, L. B. (1985). The Disaster Victim Community: Part of the solution, not the problem. *Review of Policy Research*, 4(4), 689-697.

Noguera, P. A. (2001). Transforming urban schools through investments in the social capital of parents. *Psychology,* 16, 725-50.

Norris, F. H., Sherrieb, K., and Galea, S. (2010). Prevalence and consequences of disaster-related illness and injury from Hurricane Ike. *Rehabilitation Psychology,* 55(3), 221.

Norris, F. H., Stevens, S. P., Pfefferbaum, B., Wyche, K. F., and Pfefferbaum, R. L. (2008). Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American Journal of Community Psychology,* 41(1-2), 127-150.

Paton, D., and Johnston, D. (2001). Disasters and communities: vulnerability, resilience and preparedness. *Disaster Prevention and Management: An International Journal*, 10(4), 270-277.

Paton, D., Bajek, R., Okada, N., and McIvor, D. (2010). Predicting community earthquake preparedness: a cross-cultural comparison of Japan and New Zealand. *Natural Hazards*, 54(3), 765-781.

Patterson, J. M. (2002). Understanding family resilience. *Journal of Clinical Psychology*, 58(3), 233-246.

Pattillo, M. E. (1998). Sweet mothers and gangbangers: Managing crime in a black middle-class neighborhood. *Social Forces*, *76*(3), 747-774.

Peacock, W. G., Dash, N., and Zhang, Y. (2006). Sheltering and housing recovery following disaster. In H. E. Rodriguez, L. Quarantelli, & R. R. Dynes (Eds.), *Handbook of disaster research* (pp. 258–274). New York: Springer

Perry, R. W., and Lindell, M. K. (2003). Understanding citizen response to disasters with implications for terrorism. *Journal of Contingencies and Crisis Management*, 11(2), 49-60.

Perry, R.W., and Quarantelli, E.L. (2005). *What is a Disaster? New Answers to Old Questions*. Xlibris, New York, NY

Peterson, R. D., Krivo, L. J., and Hagan, J. (2010). Divergent social worlds. *New York: Russell Sage Foundation*.

Peterson, R., and Krivo, L. (1999). Racial segregation, the concentration of disadvantage, and black and white homicide victimization. *Sociological Forum*, 14(3), 465-493.

Portes, A. (1998). Social Capital: Its Origins and Applications in Modern Society. *Annual Review of Sociology*, 24, 1-24.

Portes, A. & Vickstrom, E. (2011). Diversity, Social Capital and Cohesion. *Annual Review of Sociology* 37, 461-479.

Putnam, R. (2000) *Bowling Alone: The Collapse and Revival of American Community*. New York: Simon and Schuster.

Putnam, R. D. (2007). E pluribus unum: Diversity and community in the twenty□first century the 2006 Johan Skytte Prize Lecture. *Scandinavian Political Studies*, 30(2), 137-174.

Quarantelli, E.L. (2000). Disaster Research. In E.F. Borgatta and R.J.V. Montgomery (Eds.) *Encyclopedia of Sociology*, edited by. New York, NY: Macmillan, pp. 682-688.

Quarantelli, E.L. (1989). Conceptualizing disasters from a sociological perspective. *International Journal of Mass Emergencies and Disasters* 7, 243–251.

Quarantelli, E. L., and Dynes, R. R. (1977). Response to social crisis and disaster. *Annual Review of Sociology*, 3, 23-49.

Ritchie, L.A. (2004). *Voices of Cordova: Social Capital in the Wake of the Exxon Valdez oil Spill*. Ph.D. Dissertation, Department of Sociology, Anthropology, and Social Work, Mississippi State University.

Ritchie, L.A., Gill, D.A. (2010). Fostering resiliency in renewable resource communities: subsistence lifescapes and social capital. In: Rivera, J.D., Miller, D.S. (Eds.), *How Ethnically Marginalized Americans Cope with Catastrophic Disasters: Studies in Suffering and Resiliency*. Edwin Mellen Press, Lewiston, NY, pp. 51–81.

Ritchie, L.A., Gill, D.A. (2007). Social capital theory as an integrating theoretical framework in technological disaster research. *Sociological Spectrum* 27, 103–129.

Sampson, R. (1999). "What "Community" Supplies. Pp. 241- 292 in *Urban Problems and Community Development*, edited by Ronald Ferguson and William T. Dickens. Washington: The Brookings Institution.

Sampson, R. (2001). Crime and Public Safety: Insights from Community-Level Perspectives on Social Capital. In S. Saegert, J. P. Thompson and M. R. Warren in *Social Capital and Poor Communities (*pp. 89-114). New York: Russell Sage Foundation.

Sampson, R. (2012). *Great American City: Chicago and the Enduring Neighborhood Effects*. Chicago: The University of Chicago Press.

Sampson, R. J. (2013). The place of context: a theory and strategy for criminology's hard problems. *Criminology*, 51(1), 1-31.

Sampson, R. J., Morenoff, J. D., and Earls, F. (1999). Beyond social capital: Spatial dynamics of collective efficacy for children. *American Sociological Review*, 64(5), 633-660.

Sampson, R. J., Morenoff, J. D., and Gannon-Rowley, T. (2002). Assessing" neighborhood effects": Social processes and new directions in research. *Annual Review of Sociology*, 28, 443-478.

Sampson, R. J., Raudenbush, S. W., and Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, 277(5328), 918-924.

Satorra, A., & Bentler, P. M. (2001). A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika*, 66(4), 507-514.

Shaw, C. R., and McKay, H.D. (1942). *Juvenile Delinquency and Urban Areas*. Chicago: University of Chicago Press.

Steenbeek, W., and J. Hipp. (2011). A Longitudinal Test of Social Disorganization Theory: Feedback Effects Among Cohesion, Social Control and Disorder. *Criminology*, 49(3):833–71.

Sweet, S. (1998). The effect of a natural disaster on social cohesion: A longitudinal study. *International Journal of Mass Emergencies and Disasters, 16*(3), 321-331.

Taylor, R. B. (2015). *Community criminology: Fundamentals of spatial and temporal scaling, ecological indicators, and selectivity bias*. NYU Press.

Van Aalst, M. K. (2006). The impacts of climate change on the risk of natural disasters. *Disasters, 30*(1), 5-18.

Weisburd, D. L., Groff, E. R., and Yang, S. M. (2012). *The criminology of place: Street segments and our understanding of the crime problem*. Oxford University Press.

Wickes, R. L. (2010). Generating action and responding to local issues: Collective efficacy in context. *Australian & New Zealand Journal of Criminology*, *43*(3), 423-443.

Wickes, R., Zahnow, R., Taylor, M., and Piquero, A. R. (2015). Neighborhood Structure, Social Capital, and Community Resilience: Longitudinal Evidence from the 2011 Brisbane Flood Disaster. *Social Science Quarterly, 96*(2), 330-353.

Wickes, R., Zahnow, R., White, G., and Mazerolle, L. (2013). Ethnic diversity and its impact on community social cohesion and neighborly exchange. *Journal of Urban Affairs, 36*(1), 51-78.

Wilson, W. J. (1987). *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago: University of Chicago Press.

Zottarelli, L. K. (2008). Post-Hurricane Katrina Employment Recovery: The Interaction of Race and Place. *Social Science Quarterly*, 89(3), 592-607.

7.0 Appendices

7.1 ACCS Survey Items Waves 2, 3 and 4

Collective efficacy	Reciprocated Exchange	Social Cohesion Scale
How likely is it that people in your neighborhood would do something if:	1. How often do you and people in your neighborhood do favors for each other?	1. People around here are willing to help their neighbors.
1. …a group of neighborhood children were skipping school	2. How often do you and people in your neighborhood visit in each other's homes or on the street?	2. This is a close-knit neighborhood.
2. …some children were spray painting graffiti	3. How often do you and people in your neighborhood ask each other for advice about personal things such as child rearing or job openings?	3. People in this neighborhood can be trusted.
3. …there was a fight in front of your house		4. People in this neighborhood do not share the same values.
4. …a child was showing disrespect		
5. …someone was publicly dealing drugs in your neighborhood		
6. …someone was drunk in public in your neighborhood		
7. …people were speeding in cars along the streets in your neighborhood		
8. …somebody was getting mugged		

7.2 Univariate Statistics

Appendix 2: Descriptive Statistics for Survey Items: Means (Standard Deviations)

	Wave 2			Wave 3			Wave 4		
		Flooded			Flooded			Flooded	
Item	Total	No	Yes	Total	No	Yes	Total	No	Yes
Social Cohesion									
Item 1	4.10 (0.83)	4.13 (0.82)	4.06 (0.85)	4.05 (0.80)	4.07 (0.79)	4.03 (0.81)	4.12 (0.75)	4.10 (0.75)	4.14 (0.74)
Item 2	3.55 (1.11)	3.59 (1.11)	3.47 (1.13)	3.60 (1.03)	3.62 (1.03)	3.55 (1.03)	3.64 (1.00)	3.63 (1.01)	3.66 (0.98)
Item 3	3.87 (0.86)	3.87 (0.86)	3.87 (0.86)	3.80 (0.85)	3.82 (0.84)	3.76 (0.86)	3.83 (0.84)	3.82 (0.85)	3.84 (0.83)
Item 4	3.49 (1.01)	3.49 (1.00)	3.48 (1.01)	3.17 (1.04)	3.18 (1.04)	3.16 (1.05)	3.18 (1.06)	3.17 (1.06)	3.19 (1.06)
N	4,084	2,830	1,254	4,319	2,942	1,377	4,084	2,824	1,260
Reciprocated Exchange									
Item 1	3.13 (0.85)	3.14 (0.84)	3.11 (0.85)	3.18 (0.90)	3.20 (0.89)	3.14 (0.90)	3.17 (0.87)	3.16 (0.89)	3.21 (0.84)
Item 2	2.96 (0.96)	2.98 (0.94)	2.92 (1.00)	2.98 (0.96)	3.00 (0.95)	2.96 (0.97)	2.99 (0.94)	2.97 (0.94)	3.01 (0.93)
Item 3	2.51 (1.08)	2.52 (1.09)	2.48 (1.08)	2.30 (1.05)	2.32 (1.06)	2.26 (1.03)	2.24 (1.05)	2.25 (1.06)	2.22 (1.02)
N	4,025	2,788	1,237	4,314	2,935	1,379	4,075	2,825	1,250
Collective Efficacy									
Item 1	3.25 (1.36)	3.22 (1.36)	3.30 (1.36)	3.28 (1.32)	3.27 (1.32)	3.29 (1.32)	3.43 (1.30)	3.40 (1.31)	3.48 (1.27)
Item 2	4.22 (1.01)	4.22 (1.01)	4.23 (1.02)	4.14 (1.03)	4.16 (1.02)	4.11 (1.06)	4.24 (0.99)	4.22 (1.01)	4.29 (0.94)
Item 3	3.88 (1.21)	3.89 (1.20)	3.84 (1.22)	3.89 (1.17)	3.92 (1.16)	3.81 (1.20)	3.93 (1.15)	3.95 (1.14)	3.89 (1.17)
Item 4	2.96 (1.24)	2.98 (1.23)	2.90 (1.26)	2.91 (1.19)	2.93 (1.20)	2.87 (1.17)	2.98 (1.20)	2.98 (1.21)	2.89 (1.17)
Item 5	4.09 (1.11)	4.10 (1.09)	4.07 (1.14)	4.02 (1.10)	4.03 (1.10)	4.00 (1.12)	4.05 (1.09)	4.04 (1.10)	4.08 (1.07)
Item 6	2.91 (1.22)	2.92 (1.21)	2.88 (1.22)	2.98 (1.18)	2.98 (1.18)	2.99 (1.17)	3.07 (1.17)	3.08 (1.17)	3.05 (1.17)
Item 7	3.76 (1.24)	3.77 (1.24)	3.72 (1.25)	3.73 (1.20)	3.76 (1.21)	3.67 (1.20)	3.85 (1.15)	3.84 (1.18)	3.87 (1.10)
Item 8	4.07 (0.95)	4.07 (0.95)	4.07 (0.94)	4.01 (0.95)	4.03 (0.93)	3.97 (0.99)	4.09 (0.93)	4.08 (0.93)	4.09 (0.93)
N	4,081	2,825	1,256	4,225	2,875	1,350	4,014	2,772	1,242

7.3 Coefficients from analyses

Appendix 3: Coefficient Estimates and Standard Errors for Best Fitting Models

Panel A: Social Cohesion and Trust (SCT)

Within Level		
Measurement Model	Estimate	S.E.
Wave 2		
This is a close-knit neighborhood.	1.000#	
People around here are willing to help their neighbors.	0.702***	0.026
People in this neighborhood can be trusted.	0.594***	0.027
People in this neighborhood do not share the same values.	0.460***	0.024
Wave 3		
This is a close-knit neighborhood.	1.000#	
People around here are willing to help their neighbors.	0.707***	0.018
People in this neighborhood can be trusted.	0.601***	0.019
People in this neighborhood do not share the same values.	0.310***	0.022
Wave 4		
This is a close-knit neighborhood.	1.000#	
People around here are willing to help their neighbors.	0.681***	0.021
People in this neighborhood can be trusted.	0.626***	0.024
People in this neighborhood do not share the same values.	0.330***	0.029
Structural Model		
Covariate		
SCT Wave 3 ON SCT Wave 2	0.774***	0.018
SCT Wave 4 ON SCT Wave 3	0.774***	0.018
Between Level		
Measurement Model		
This is a close-knit neighborhood. (Wave 2)	1.000#	
People around here are willing to help their neighbors. (Wave 2)	1.440***	0.118
People in this neighborhood can be trusted. (Wave 2)	1.453***	0.133
People in this neighborhood do not share the same values. (Wave 2)	1.186***	0.132
This is a close-knit neighborhood. (Wave 3)	0.880***	0.077
People around here are willing to help their neighbors. (Wave 3)	1.231***	0.104
People in this neighborhood can be trusted. (Wave 3)	1.631***	0.155
People in this neighborhood do not share the same values. (Wave 3)	1.282***	0.157
This is a close-knit neighborhood. (Wave 4)	0.886***	0.092
People around here are willing to help their neighbors. (Wave 4)	1.232***	0.110
People in this neighborhood can be trusted. (Wave 4)	1.544***	0.132
People in this neighborhood do not share the same values. (Wave 4)	1.434***	0.132
Structural Model		
Social Cohesion and Trust ON:		
Concentrated Disadvantage	-0.079***	0.008

Median Income	0.030*	0.013
Residential Stability	-0.018*	0.007
Ethnic Diversity	-0.129*	0.060

Notes: # Coefficient estimate fixed at 1.000 to set the scale for the latent variable; *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$

Panel B: Reciprocated Exchange (RE)

Within Level		
Measurement Model	Estimate	S.E.
Wave 2		
How often do you and people in your neighborhood visit in each other's homes or on the street?	1.000#	
How often do you and people in your neighborhood do favors for each other?	0.845***	0.025
How often do you and people in your neighborhood ask each other for advice about personal things such as child rearing or job openings?	1.044***	0.023
Wave 3		
How often do you and people in your neighborhood visit in each other's homes or on the street?	1.000#	
How often do you and people in your neighborhood do favors for each other?	0.838***	0.018
How often do you and people in your neighborhood ask each other for advice about personal things such as child rearing or job openings?	0.851***	0.021
Wave 4		
How often do you and people in your neighborhood visit in each other's homes or on the street?	1.000#	
How often do you and people in your neighborhood do favors for each other?	0.818***	0.022
How often do you and people in your neighborhood ask each other for advice about personal things such as child rearing or job openings?	0.824***	0.022
Structural Model		
Covariate		
RE Wave 3 ON RE Wave 2	0.815***	0.018
RE Wave 4 ON RE Wave 3	0.815***	0.018
Between Level		
Measurement Model		
How often do you and people in your neighborhood do favors for each other? (Wave 2)	1.000#	
How often do you and people in your neighborhood visit in each other's homes or on the street? (Wave 2)	1.075***	0.110
How often do you and people in your neighborhood ask each other for advice about personal things such as child rearing or job openings? (Wave 2)	0.966***	0.081
How often do you and people in your neighborhood do favors for each other? (Wave 3)	1.263***	0.110
How often do you and people in your neighborhood visit in each other's homes or on the street? (Wave 3)	1.112***	0.112

How often do you and people in your neighborhood ask each other for advice about personal things such as child rearing or job openings? (Wave 3)	0.899***	0.175
How often do you and people in your neighborhood do favors for each other? (Wave 4)	1.212***	0.106
How often do you and people in your neighborhood visit in each other's homes or on the street? (Wave 4)	1.034***	0.111
How often do you and people in your neighborhood ask each other for advice about personal things such as child rearing or job openings? (Wave 4)	0.884***	0.159
Structural Model		
Reciprocated Exchange ON:		
Not Flooded		
Concentrated Disadvantage	0.000	0.013
Median Income	-0.039	0.017*
Residential Stability	-0.584	0.107***
Ethnic Diversity	0.095	0.024***
Flooded		
Concentrated Disadvantage	-0.012	0.013
Median Income	0.005	0.018
Residential Stability	-0.364	0.112***
Ethnic Diversity	0.077	0.025**

Notes: # Coefficient estimate fixed at 1.000 to set the scale for the latent variable; $*p \leq 0.05$, $**p \leq 0.01$, $***p \leq 0.001$

Panel C: Collective Efficacy (CE)

Within Level		
Measurement Model		
How likely is it that people in your neighborhood would do something if:		
Wave 2	Estimate	S.E.
a group of neighborhood children were skipping school	1.000#	
some children were spray painting graffiti	0.882***	0.035
there was a fight in front of your house	0.757***	0.048
a child was showing disrespect	0.753***	0.041
someone was publicly dealing drugs in your neighborhood	0.864***	0.042
someone was drunk in public in your neighborhood	0.871***	0.038
people were speeding in cars along the streets in your neighborhood	0.857***	0.038
somebody was getting mugged	0.751***	0.038
Wave 3		
a group of neighborhood children were skipping school	1.000#	
some children were spray painting graffiti	0.880***	0.031
there was a fight in front of your house	0.820***	0.042
a child was showing disrespect	0.820***	0.032
someone was publicly dealing drugs in your neighborhood	0.896***	0.036
someone was drunk in public in your neighborhood	0.920***	0.038
people were speeding in cars along the streets in your neighborhood	0.908***	0.039
somebody was getting mugged	0.763***	0.036
Wave 4		
a group of neighborhood children were skipping school	1.000#	
some children were spray painting graffiti	0.840***	0.030
there was a fight in front of your house	0.726***	0.041
a child was showing disrespect	0.787***	0.033
someone was publicly dealing drugs in your neighborhood	0.908***	0.038
someone was drunk in public in your neighborhood	0.880***	0.041
people were speeding in cars along the streets in your neighborhood	0.893***	0.043
somebody was getting mugged	0.714***	0.035
Structural Model		
Covariate		
Not Flooded		
CE Wave 3 ON CE Wave 2	0.730***	0.038
CE Wave 4 ON CE Wave 3	0.824***	0.041
Flooded		
CE Wave 3 ON CE Wave 2	0.844***	0.050

CE Wave 4 ON CE Wave 3	0.855***	0.054
Between Level		
Measurement Model		
How likely is it that people in your neighborhood would do something if:		
a group of neighborhood children were skipping school (Wave 2)	1.000#	
some children were spray painting graffiti (Wave 2)	0.703***	0.049
there was a fight in front of your house (Wave 2)	0.512***	0.062
a child was showing disrespect (Wave 2)	0.289***	0.055
someone was publicly dealing drugs in your neighborhood (Wave 2)	0.568***	0.069
someone was drunk in public in your neighborhood (Wave 2)	0.338***	0.056
people were speeding in cars along the streets in your neighborhood (Wave 2)	0.393***	0.058
somebody was getting mugged (Wave 2)	0.457***	0.049
a group of neighborhood children were skipping school (Wave 3)	1.065***	0.068
some children were spray painting graffiti (Wave 3)	0.821***	0.059
there was a fight in front of your house (Wave 3)	0.540***	0.073
a child was showing disrespect (Wave 3)	0.414***	0.054
someone was publicly dealing drugs in your neighborhood (Wave 3)	0.675***	0.097
someone was drunk in public in your neighborhood (Wave 3)	0.348***	0.055
people were speeding in cars along the streets in your neighborhood (Wave 3)	0.528***	0.072
somebody was getting mugged (Wave 3)	0.531***	0.055
a group of neighborhood children were skipping school (Wave 4)	1.049***	0.070
some children were spray painting graffiti (Wave 4)	0.780***	0.061
there was a fight in front of your house (Wave 4)	0.517***	0.063
a child was showing disrespect (Wave 4)	0.524***	0.061
someone was publicly dealing drugs in your neighborhood (Wave 4)	0.697***	0.081
someone was drunk in public in your neighborhood (Wave 4)	0.431***	0.061
people were speeding in cars along the streets in your neighborhood (Wave 4)	0.449***	0.065
somebody was getting mugged (Wave 4)	0.448***	0.044
Structural Model		
Collective Efficacy ON:		
Not Flooded		
Concentrated Disadvantage	-0.137***	0.019
Median Income	-0.054	0.031
Residential Stability	-0.611***	0.154
Ethnic Diversity	0.104**	0.039

Flooded		
Concentrated Disadvantage	-0.092***	0.026
Median Income	0.028	0.032
Residential Stability	-0.808***	0.206
Ethnic Diversity	0.188***	0.048

Notes: # Coefficient estimate fixed at 1.000 to set the scale for the latent variable; *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$