PREVENTING NEIGHBORHOOD DISORDER:

THE ROLE OF MUTUAL EFFICACY IN COLLECTIVE EFFICACY THEORY

By

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- Abraham Lincoln

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Preventing Neighborhood Disorder:

The Role of Mutual Efficacy in Collective Efficacy Theory

Abstract

by

MICHAEL C. GEARHART

Neighborhood disorder is a social welfare issue that is associated with multiple negative outcomes for individuals including increased substance use, increased exposure to violence and crime, and mental health challenges. Collective efficacy is a widely studied predictor of positive community-level outcomes including lower levels of neighborhood disorder. However, relatively few community interventions based on collective efficacy have been developed. Further, studies evaluating interventions based on collective efficacy have reported mixed findings. A possible reason for the difficulty of operationalizing collective efficacy may be our current conceptualization of collective efficacy. The current understanding of collective efficacy views the concept as a combination of social cohesion and informal social control. However, recent research suggests that social cohesion and informal social control are unique constructs that are best conceptualized and measured separately. Further, research suggests that there may be factors that mediate the relationship between social cohesion and informal social control.

This dissertation seeks to advance our understanding of collective efficacy in order to increase its utility for social work practice. A key component of collective efficacy is a community's *shared belief* that collective action will be successful. Although this belief has been discussed conceptually, it has yet to be measured in collective efficacy research. To address this limitation, I develop a concept called, "Mutual efficacy," which is defined as, "community members' beliefs that collective action will be successful at attaining group goals."

This dissertation utilizes data from the Seattle Neighborhood and Crime Survey (SNCS) to explore mutual efficacy's role as a mediator between social cohesion and informal social control. The SNCS is a survey of 3,365 residents in Seattle, Washington. The factor structure of social cohesion, mutual efficacy, and informal social control were studied using exploratory factor analysis and multilevel confirmatory factor analysis. A structural model was then used to test whether or not mutual efficacy mediates the relationship between social cohesion and informal social control, and if this model predicted lower levels of neighborhood disorder. This mediation model (referred to as the mutual efficacy model) was then compared to the current model of collective efficacy.

The results from both factor analyses suggest that mutual efficacy is a concept that is unique from, but positively associated with social cohesion and informal social control. Further, mutual efficacy partially mediates the relationship between social cohesion and informal social control. The mutual efficacy model also predicted lower levels of neighborhood disorder and fit the data better than the current model of collective efficacy. These findings can inform community practice that seeks to facilitate collective

action in communities. The results also highlight a need to conduct further research on mutual efficacy.

Chapter 1 – Introduction

This dissertation is comprised of six chapters. Chapter 1 will frame neighborhood disorder as a social welfare issue, introduce key concepts, and state the research questions that guide this dissertation. Chapter 2 will review the conceptual and empirical literature pertaining to collective efficacy and neighborhood disorder, and critique collective efficacy as a community practice theory. Chapter 3 will describe the conceptual and operational definitions of a new concept called "mutual efficacy," and propose a modified model of collective efficacy where mutual efficacy mediates the relationship between social cohesion and informal social control. Chapter 4 will then describe the methodology to be used to answer the research questions. Chapter 5 will present the results based on each research question and describe the limitations of this dissertation. Chapter 6 will provide a discussion based on the findings of this dissertation.

Chapter 1 begins by framing neighborhood disorder as a social welfare issue and introduces key concepts. The chapter then describes neighborhood disorder's impact on both individuals and neighborhoods. Then Chapter 1 describes and critiques the traditional policy response to neighborhood disorder. Evidence pertaining to social work's efforts to raise collective efficacy will also be described. The chapter concludes by providing a brief discussion of the methods that will be used in this dissertation including a description of the data, and the research questions and hypotheses that guide this dissertation.

Introduction

An enduring goal of community-based social change is to promote better outcomes for individuals by improving the communities they live in. Neighborhood disorder can be considered a social welfare issue because it is associated with individual outcomes like poor physical health, mental illness, substance use, and criminal justice involvement (Chappell, Monk-Turner, & Payne, 2011; Dubowitz et al., 2014; Molina, Algria, & Chen, 2012) and neighborhood issues like high crime rates, lower levels of trust among residents, and an increased desire to leave the neighborhood **(**Hill & Maimon, 2013**)**. Neighborhood disorder refers to public behaviors that are threatening to residents such as public intoxication, and physical markers like garbage on the streets, graffiti, and abandoned buildings (Sampson, 2012). Not only is neighborhood disorder part of the cause of a variety of social issues, but it can also moderate the buffering effect of protective factors like collective efficacy (Hill & Maimon, 2013).

Collective efficacy has been defined as the, "Shared beliefs in neighbors' conjoint capability for action to achieve an intended effect" (Morenoff, Sampson & Raudenbush, 2001, p. 521). Collective efficacy is comprised of two concepts: Social cohesion and informal social control. Social cohesion is defined by Sampson, Morenoff, and Earls (1997) as trust among neighbors, reciprocal helping behavior, and shared values among neighbors. Informal social control focuses a community's willingness to enforce social norms in the local area (Bursik & Grasmick, 1993; Sampson et al., 1997). Because communities with higher levels of social cohesion do not always institute informal social control (Bursik, 1986), Sampson and colleagues (1997) examined the relationship between these constructs using data from small neighborhood areas in Chicago. They found that social cohesion and informal social control were highly correlated, so the authors combined them into one concept – collective efficacy. Since its first use in published research (Sampson et al., 1997), collective efficacy has been a widely studied predictor of neighborhood disorder (Armstrong, Katz & Schnebly, 2010; Burchfield & Silver, 2013; Cagney, Glass, Skarupski, Barnes, Schwartz & de Leon, 2009; Cohen, Finch, Bower, & Sastry, 2006; Galster & Santiago, 2006; Hinkle, 2009; 2013; Jackson, Gray, & Brunton-Smith, 2010; O'Brien & Kauffman, 2013; Sampson, 2012; Sampson & Morenoff, 1999; Sampson, Morenoff, & Earls, 1999; Sampson & Raudenbush, 2004; Simons, Simons, Burt, Brody, & Curtona, 2005; Steenbeek & Hipp, 2011; Velez, 2001; Way, Finch, & Cohen, 2006).

Although the combining social cohesion and informal social control is common in previous research, more recent studies suggest that the relationship between the two is nuanced and requires more careful analytical treatment. For example, recent factor analyses of collective efficacy suggest that social cohesion and informal social control are better represented as two separate factors (Armstrong et al., 2010; Brisson & Altschul, 2011; Wickes, Hipp, Sargeant, & Homel, 2013). Separating these concepts makes it possible to study variables that may mediate or moderate the relationship between them. Uncovering mediators are important for social work practice because they provide practitioners with more targets for intervention and help researchers better understand how and why collective action occurs in communities.

This study will develop a new concept called "mutual efficacy." I define mutual efficacy as, "Community members' beliefs that collective action will be successful at attaining group goals." Rooted in the work of Bandura (1997) and Sampson (2012), mutual efficacy states that communities with a *shared belief* that collective action will be successful are more likely to act. A modified model of collective efficacy where mutual efficacy mediates the relationship between social cohesion and informal social control will be developed in this dissertation (see Appendix A for an illustration). In short, while social cohesion indicates that community members feel that they share some collective identity and interests, mutual efficacy indicates that members believe that if they work collectively, they will be successful at addressing neighborhood issues. Because of this belief, community members are expected to be more likely to work together and generate informal social control. Mutual efficacy and the modified model of collective efficacy will be described in greater detail in Chapter 3.

The Impact of Neighborhood Disorder on Individuals

Research has consistently shown that neighborhood disorder is concentrated within certain neighborhoods (Sampson, 2006; Sharkey, 2014; Shaw & McKay, 1942, 1969; Wilson, 1987). Sampson (2012) demonstrates that levels of neighborhood disorder vary widely across neighborhoods. However, respondents' perceptions of neighborhood disorder are highly correlated *within* neighborhoods ($r = 0.89$, $p < .01$). High levels of neighborhood disorder have a negative impact on residents living in these neighborhoods. For example, adults who witness disorder are more likely to use substances like alcohol or other drugs (Galea, Ahern, Tracy, & Vlahov, 2007; Molina et al., 2012; Silver, Mulvey & Swansons, 2002). Similar trends have been observed in youth (Burlew, Johnson, Peteet, Griffith-Henry, & Buchanan, 2009). Youth are also more likely to start using substances at a younger age if they live in neighborhoods with higher levels of neighborhood disorder (Burlew, et al., 2009; Tucker, Pollard, de la Hay, Kennedy, & Green, 2013; Wilson, Syme, Boyce, Battistich, & Selving, 2005; Witansley, Steinwachs, Ensminger, Latkin, Stitzer, & Olsen, 2008).

Increased substance use in disorderly neighborhoods present a public health concern due to the elevated risk of mortality related to substance use (e.g. overdose; Galea & Vlahov, 2002), and an increased likelihood of contracting sexually transmitted diseases through needle sharing behaviors (Caciano & Massey, 2008; Latkin, German, Vlahov & Galea, 2013). Further, residents are less likely to exercise in neighborhoods with higher levels of disorder, and typically have limited access to quality food (Wei, Hipwell, Pardini, Beyers & Loeber, 2005; Dubowitz et al., 2014). These factors place residents at a greater risk of contracting physical health issues like hypertension, diabetes, asthma, and cancer (Cohen, Mason, Bedimo, Scribner, Basolo, & Farley, 2003; Van Slujis, McMinn, & Griffin, 2007). Ultimately, these issues may contribute to the poor health and quality of life of residents in disorderly neighborhoods (Chappell et al., 2011; Taylor, 2001).

Not only has neighborhood disorder been shown to have an impact on physical health, but it can impact the mental health of residents as well (Hill & Maimon, 2013). Residents living in these neighborhoods are at an increased risk of experiencing negative life events like interactions with substance users, and fighting (Cutrona, Wallace & Wesner, 2006; Hill, Ross, & Angel, 2005; Ross & Mirowsky, 2009). Youth in disorderly neighborhoods are also at a greater risk of being exposed to violence and child abuse (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007; Turner, Finkelhor, & Ormrod, 2006). These negative life events place residents at risk for developing mental health issues like post-traumatic stress disorder and depression (Cutrona et al., 2006; Hill et al., 2005; Ross & Mirowsky, 2009).

Social support is a protective factor that has been shown to buffer the negative impact of neighborhood disorder on individual level outcomes like substance use, mental health, and physical health (Maimon & Browning, 2010; Cutrona et al., 2005; Hill et al., 2005; Ross & Mirowsky, 2009; Sampson et al., 2002). Social support refers to the psychological and material resources in social networks that help individuals cope with stress (Cohen, 2004). Social support is typically lower in neighborhoods with higher levels of disorder (Browning, Soller, Gardner, Brooks-Gunn, 2013; Hill, Burdette, Jokinen-Gordon, & Brailsford, 2013; Ross & Mirowsky, 2009; Turner, Shattuck, Hamby, & Finkelhor, 2013). This is due to the fact that residents in disorderly neighborhoods are more likely to mistrust one another and feel a sense of powerlessness (Hipp, Tita, & Greenbaum, 2009; McCrea, Stimson, & Western, 2005; Oh, 2003; Ross, Mirowski, & Pribesh, 2001). However, neighborhood disorder also moderates the relationship between social support and outcomes (Hill & Maimon, 2013; Kim, 2010; McMahon et al., 2011). This means that even if social support is high, its impact on individuals will be weaker in disorderly neighborhoods (Hill & Maimon, 2013; Kim, 2010; McMahon et al., 2011).

The Impact of Neighborhood Disorder on the Neighborhood

In addition to neighborhood disorder's impact on the individual level, neighborhood disorder also has a negative impact on neighborhood level social processes, physical development, and socioeconomic trends. Although there are some who contend that neighborhood disorder can have a positive impact when residents organize to reduce neighborhood disorder (Perkins, Florin, Rich, Wandersman & Chavis, 1990; Taylor, 1996), the more common response to neighborhood disorder is a downward spiral where the economic and social resources necessary to mobilize against disorder are depleted, resulting in even more disorder (Bursik, 1986; Chan, 2001; Schuerman & Kobrin, 1986; Skogan, 1986, 1990; Steenbeek & Hipp, 2011; Wilson, 1987). Some have labeled this process as a spiral of decay (Keizer, Lindenberg, & Steg, 2008; Wallace, Hedberg, & Katz, 2012; Wallace & Schalliol, 2015). This process will be described in the following paragraphs.

Residents living within neighborhoods that have high levels of neighborhood disorder typically report an increased desire to leave the neighborhood (Hipp, Tita, & Greenbaum, 2009; McCrea, Stimson, & Western, 2005; Oh, 2003; Ross, Mirowski, & Pribesh, 2001). However, more affluent residents are the most likely to leave neighborhoods with higher levels of neighborhood disorder (Crowder, 2001; Flippen, 2004; Hipp, 2010; Jargowsky, 1997; Myers, 1999, 2000; Ng, Muntaner, Chung & Eaton, 2014; Park & Burgess, 1925; Sampson & Wilson, 1995; South & Crowder, 1998). Businesses often follow the more affluent residents in this outward migration, removing employers and services like grocery stores from the neighborhood (Grayson & Young, 1994; Rogerson, 1999; Sirgy & Cornwell, 2002; Wilson, 1987, 2011).

Neighborhood disorder also serves as a barrier in terms of attracting new residents and businesses into a neighborhood (Garland & Stokols, 2002; Hipp, 2011; Rogerson, 1999; South & Crowder, 1997; Turner, Ross, Galser, & Yinger, 2002; Wilson, 2011). Because more affluent residents and businesses are less likely to move into disorderly neighborhoods, the housing markets in these neighborhoods are typically limited to impoverished minority groups (Flippen, 2004; Sampson & Wilson, 1995; Shaw & McKay, 1942, 1969). This restriction in the number of potential neighborhood occupants results in multiple abandoned properties, the concentration of low income residents in certain neighborhoods within a city, and limited tax revenues available for developing the neighborhood due to vacant properties (Park & Burgess, 1925; Shaw & McKay, 1942, 1969; Wilson, 1987, 2011).

Not only does neighborhood disorder impact the economic capital of a neighborhood, it depletes collective efficacy as well (Brown, Perkins, & Brown, 2003; McCrea et al., 2005; Sampson, 2012; Sampson et al., 1997; Taylor, 2002). As outlined above, neighborhood disorder increases population mobility. This limits the number of opportunities to form networks among residents, and decreases community attachment (Bourdieu, 1985; Coleman, 1988; Conklin, 1975; Sampson & Groves, 1989; Sampson et al., 1997; Sampson et al., 1999). Community attachment encourages neighbors to form bonds with one another (Brown & Perkins, 1992; Brown et al., 2003; Fishman, 2000; McCrea et al., 2005; Twigger-Ross & Ussel, 1996). These bonds generate social cohesion among neighbors, which is a key component of collective efficacy (Bordieu, 1985; Bursik & Grasmick, 1993; Coleman, 1988; Duncan, Duncan, Okut, Strycker, & Hix-Small, 2003; Sampson et al., 1997; Sampson et al., 1999; Sampson, 2006, 2012; Taylor, 2002). Residents living in disorderly neighborhoods also feel higher levels of powerlessness, reducing the likelihood that they will informally monitor their neighborhoods (Hinkle, 2009, 2013; Hinkle & Yang, 2014; Skogan, 1990). In short, neighborhood disorder undermines the two key components of collective efficacy: social cohesion and informal social control.

Traditional Policy Response to Neighborhood Disorder

A popular framework informing policy responses to neighborhood disorder is broken windows theory. Broken windows theory states that neighborhood disorder leads to a sense of powerlessness among residents, which in turn leads to crime (Wilson & Kelling, 1982). These indicators of accumulate, resulting in more disorder and crime in the community (Wilson, 1987). Policing minor transgressions is typically viewed as a method for preventing crime (Wilson & Kelling, 1982). Therefore, initiatives informed by broken windows theory typically advocate for aggressively policing neighborhoods with higher levels of disorder (Clear, 2007; Kelling & Sousa, 2001; Mauer, 2006; Weisburd & Braga, 2006). The primary criticisms of this approach is that it is costly, counterproductive, and does not address social issues that are at the core of social problems like lower levels of collective efficacy (Braga & Brunson, 2015; Clear, 2007; Mauer, 2006; Sampson, 2006, 2012). These issues will be described in the following paragraphs.

Research examines the negative impact that aggressive police strategies have on neighborhoods (Clear, 2007; Clear, Rose, Waring & Scully, 2003; Frost & Gross, 2012; Mauer, 2006). This research suggests that mass incarceration is not an effective method for reducing neighborhood crime rates because incarcerating a large proportion of neighborhood residents creates a form of resident mobility that is caused by the criminal justice system – otherwise known as coercive mobility (Clear et al., 2003; Frost & Gross, 2012). As stated previously, resident mobility prevents residents from forming bonds with one another, which is a prerequisite for the development of collective efficacy (Clear et al., 2003; Flipp, 2004; Frost & Gross, 2012; Hipp, 2010).

Research also shows that negative interactions with the police decrease the likelihood that individuals will informally monitor their neighborhoods and report crimes to the police (Drakulich, Crutchfield, Matsueda, & Rose, 2012; Rose & Clear, 2004). An explanation of the strained relationships among police and residents is that entire neighborhoods are stereotyped as criminal, and are over-policed despite the fact that the majority of crime is caused by relatively few individuals (Braga & Brunson, 2015; Braga, Papachristos, & Hureau, 2010; Brunson & Gau, 2014; Papachristos, Braga, & Hureau, 2012). Because of this, neighborhood residents report feeling like perpetual targets of the police (Braga & Brunson, 2015; Papachristos et al., 2012). Although there are strategies like community policing that aim to improve relationships between law enforcement and residents (Braga & Weisburd, 2010, 2012; Weisburd, Telep, Hinkle, Eck, 2010), the quality of these programs vary and resident participation is difficult to elicit because of skepticism of the police (Braga & Brunson, 2015; Skogan, 2006; Skogan & Frydall, 2004).

One of the largest monetary costs associated with aggressive police tactics is the cost of incarcerating individuals from these neighborhoods. Since 1990, spending on corrections has been the largest item on federal, state, and local budgets as it relates to criminal justice (Sherman, 2011). In the United States, corrections accounts for 60% of criminal justice spending. This number ranges from 1.7 to nearly 5 times higher than the percentage of criminal justice spending dedicated to corrections in countries like Wales, Australia, Hong Kong, and Japan (Sherman, 2011). Research has consistently shown that spending on corrections is concentrated in small geographies within a city (Bruinsma, Pauwels, Weerman, & Bernasco, 2013; Clear, 2007; Mauer, 2006; Sampson, 2003, 2006;

Sampson & Groves, 1989; Sampson, et al., 1997; Shaw & McKay, 1942; 1969; Wilson, 1987). Gonnerman (2004) coined the term "million-dollar block" because Brooklyn, New York has a 35-block area where the cost of imprisonment is over one million dollars per block annually. Similarly, incarcerating offenders from the Brewer Park neighborhood in Detroit costs the state of Michigan $2.9 million in incarceration annually (Pew, 2009). Not only is it troubling that America spends so much money on incarcerating individuals living in disorderly neighborhoods, but also criminal justice spending often takes precedence over social service programs that could help people in those same neighborhoods (Mauer, 2006).

Aggressive police strategies are costly, have a negative impact on social networks within communities, and exacerbate the negative effects of neighborhood disorder even further (Sampson, 2012). More importantly, crime prevention strategies can only target indicators of disorder that are criminal offenses (e.g. public intoxication and graffiti), but not others like abandoned buildings. Research suggests that collective efficacy may be important in addressing both crime and social disorder (Gault & Silver, 2008; Jackson et al., 2010; O'Brien & Kauffman, 2013). Neighborhood disorder was originally conceptualized as a cause of criminal behavior in broken windows theory (Wilson & Kelling, 1982). However, Sampson and Raudenbush (2001) suggested that the relationship between the two may not be causal, though the two are correlated, with collective efficacy predicting both neighborhood disorder and crime. Later research (Gault & Silver, 2008; Jackson et al., 2010; O'Brien & Kauffman, 2013) provided empirical support for Sampson and Raudenbush's (2001) assertion. Therefore, collective efficacy is a useful theory that can help address both neighborhood disorder and crime.

Social Work and Neighborhood Disorder

Reducing neighborhood disorder is an important goal of social work practice that focuses on neighborhood change. For example, studies show that as disorder decreases, neighborhood satisfaction, neighborhood attachment, trust in neighbors, and quality of life improve (Duncan et al., 2003; Garcia et al., 2007; Messner et al., 2004; Sirgy & Cornwell, 2002); and a series of studies from New York suggest that lower levels of neighborhood disorder were a significant driving force of the city's housing market boom (Ellen, Schill, Susin, & Schwartz, 2002; Schwartz, Ellen, Voicu, & Schill, 2006; Schwartz, Susin, & Voicu, 2003). An important part of reducing neighborhood disorder is improving our understanding of the community level factors that influence neighborhood disorder (Gracia & Herrero, 2007).

Collective efficacy is a construct that can assist social workers because research consistently shows that higher levels of collective efficacy are associated with lower levels of neighborhood disorder (Galster & Santiago, 2006; Maimon & Browning, 2010; Morenoff et al., 2001; O'Brien & Kauffman, 2013; Sampson & Morenoff, 2001; Sampson et al., 2002). Further, collective efficacy has a moderating effect on the relationships among neighborhood disorder, and individual outcomes such as substance use, mental health, and physical health issues (Boardman, Finch, Ellison, Williams, & Jackson, 2001; Browning et al., 2013; Foster & Brooks-Gunn, 2013).

Despite being supported empirically as a predictor of neighborhood disorder, very few interventions focus on raising collective efficacy. A literature review reported that 20 community interventions had been tested between 1985 and 2002 (Ohmer & Korr, 2006). Further, none of these interventions focused exclusively on raising collective efficacy (Ohmer & Korr, 2006). Research since Ohmer & Korr's (2006) literature review has started to focus on developing interventions aimed at raising collective efficacy with mixed results. One study recruited residents to volunteer with a grass-roots organization (Ohmer, 2007). Findings indicated that the intervention increased residents' sense of community, and belief in the effectiveness of the organization, but failed to increase neighborhood collective efficacy (Ohmer, 2007; 2008a, 2008b; Ohmer & Beck, 2006). Another study (Ohmer et al., 2010) attempted to increase residents' capacity to intervene to prevent criminal activity through a pilot program based on restorative justice, peacemaking, and social work that focuses on communities. The intervention increased the likelihood that an individual would intervene, as well as their confidence in their ability to intervene, but did not raise collective efficacy. However, these findings should be interpreted cautiously because the outcome was based on the perceived likelihood a respondent would intervene, and the sample size was small (n = 15) (Ohmer et al., 2010).

In theory, community practice should raise collective efficacy by building networks and social cohesion among residents, and organizing communities to take action (Chambers, 2005; Nash, et al., 2005; Weil, Gamble, & Macguire, 2010). Comprehensive community initiatives (CCIs) are a promising approach in terms of raising collective efficacy (Kubisch, Auspos, Brown, & Dewar, 2010a, b). CCIs attempt to better the lives of children, youth, and families through systems-change work that engages all sectors of a community (Chaskin, 1999; Stagner & Duran, 1997). Overall, CCIs have been shown to have a positive impact in areas such as work force development, family services, and education (Kubisch et al., 2010a). Qualitative evidence also suggest that CCIs are effective at increasing resident participation in change initiatives (Kubisch et al., a, b). However, it is difficult to determine the impact that CCIs have on collective efficacy (Auspos, 2012; Beck, Ohmer, and Warner, 2012). This is due to the fact that many evaluations of CCIs lack measures of academic constructs like collective efficacy (Auspos, 2012; Peterson, 2002). Further, evaluations of CCIs often lack empirical rigor (Beck et al., 2012). Although one four-year longitudinal study of a CCI found that the initiative's impact on collective efficacy was trivial (McDonell, Ben-Arieh, & Melton, 2015, p. 89), more empirical research on the impact that interventions like CCIs have on collective efficacy is needed.

The Proposed Study

Neighborhood disorder undermines the economic and social resources necessary to develop collective efficacy, and low levels of collective efficacy are related to more neighborhood disorder (Bursik, 1986; Chan, 2001; Schuerman & Kobrin, 1986; Skogan, 1986; Steenbeek & Hipp, 2011; Taylor, 1995; Wilson, 1987). Research also suggests that neighborhood disorder affects poor neighborhoods the most, making the most disadvantaged communities even worse (Clear, 2007). Traditional policy responses exacerbate the negative impact of neighborhood disorder even more (Clear, 2007; Mauer, 2006; Rose & Clear, 2004). Further, more research is needed in order to determine the impact that community level interventions have on collective efficacy (Beck et al., 2012; Kubisch et al., 2010a, b; McDonnel et al., 2015). However, research focusing on collective efficacy suggests that the relationship between social cohesion and informal social control is more complex than previously suggested (Armstrong et al., 2010; Bellair & Browning, 2010; Brisson & Altschul, 2011; Wickes et al., 2013). Therefore, revisiting our understanding of social cohesion and informal social control is an important task for social work research because it can help inform interventions that focus on increasing resident participation in change efforts.

Community members' beliefs that collective actions can be successful are an important component of collective efficacy (Bandura, 1997; Sampson, 2012). However, this belief is not currently measured in studies of collective efficacy. Mutual efficacy will be developed in this dissertation to make the shared belief in the effectiveness of collective action more explicit in our empirical tests of collective efficacy. Exploring the role that mutual efficacy may play in mediating the relationship between social cohesion and informal social control can help inform interventions aimed at facilitating collective action in communities. The methods used to study mutual efficacy in this dissertation will be described in the following section.

Dataset and Research Questions

Although the research design will be described in depth in Chapter 4, a brief overview is provided here. Data for this dissertation are drawn from the Seattle Neighborhoods and Crime Survey (SNCS) (Matsueda, 2010). Conducted between 2002-2003, the SNCS is a cross-sectional study that used a telephone survey to collect data from all 123 Census Tracts in Seattle, Washington (Matsueda, 2010). The SNCS is a useful dataset for this dissertation because the researchers included two survey questions that reflect mutual efficacy: (1) how effective would small groups of neighbors be at resolving major problems around your neighborhood, and (2) how effective would organized neighborhood associations or community clubs be at resolving major problems around your neighborhood? Further, the SNCS was designed to test multilevel theories like collective efficacy (Matsueda, 2010). The multilevel structure of the SNCS is important because social cohesion, mutual efficacy, and informal social control are neighborhood level constructs (Sampson, 2012). Because of this, it is necessary to determine the reliability of these measures on the neighborhood level using multilevel confirmatory factor analysis (Bowen & Guo, 2011; Byrne, 2012; Kline, 2005). Research questions and hypotheses informing this dissertation as well as the statistical analyses used to answer the research questions are listed below:

RQ1: Are social cohesion, mutual efficacy, and informal social control unique factors on the individual level?

> **H1:** Social cohesion, mutual efficacy, and informal social control are unique factors that are positively correlated with each other.
>
> **Statistical analysis:** Exploratory factor analysis

RQ2: Do measures of social cohesion, mutual efficacy, and informal social control fit the data better as a one, two, or three factor model at both the individual level and neighborhood level?

> **H2:** The three factor model will fit the data better at the individual level and neighborhood level.
>
> **Statistical analysis:** Multilevel confirmatory factor analysis

RQ3: What are the relationships among social cohesion, mutual efficacy, and informal social control at the neighborhood level?

> **H3a:** A model where mutual efficacy mediates the relationship between social cohesion and informal social control (Mutual Efficacy Model; Appendix B) will fit the data better than the current collective efficacy model that combines social cohesion and informal social control (Appendix C).

Statistical analysis: Structural equation modeling

H3b: The relationship between social cohesion and informal social control will be at least partially mediated by mutual efficacy (Appendix B).

Statistical analysis: Structural equation modeling

RQ4: Does the mutual efficacy model predict neighborhood disorder?

H4: There will be a negative association between mutual efficacy and neighborhood disorder where higher levels of mutual efficacy are associated with lower levels of neighborhood disorder through mutual efficacy's relationship with informal social control.

Statistical analysis: Structural equation modeling

Conclusion – Chapter 1

The next five chapters will review the conceptual and empirical literature pertaining to collective efficacy and neighborhood disorder (Chapter 2); conceptualize and operationalize mutual efficacy, and develop a modified model of collective efficacy where mutual efficacy mediates the relationship between social cohesion and informal social control (Chapter 3); and describe the research methods to be used to test the research questions informing this study (Chapter 4). Chapter 5 will present the findings from the analyses and discuss the limitations of this dissertation. Chapter 6 will then discuss the findings and provide a conclusion based on the findings. Examining mutual efficacy's role in collective efficacy theory can advance the field by developing a mechanism (mutual efficacy) that can help practitioners mobilize residents to address neighborhood issues. Second, by demonstrating that there are variables that mediate the relationship between social cohesion and informal social control, researchers can begin to explore other variables that may contribute to our understanding of collective efficacy.

Chapter 2 – Literature Review

Chapter 2 will review the literature on collective efficacy with a focus on the relationship between neighborhood disorder and collective efficacy. The chapter begins with a discussion of the conceptual and operational definitions of neighborhood disorder. Then, Chapter 2 will describe the evolution of collective efficacy beginning with social disorganization and then social capital, social cohesion, and informal social control. Collective efficacy will be defined conceptually and operationally. Then the empirical findings related to neighborhood disorder and collective efficacy will be summarized, and community structural factors that impact collective efficacy will be discussed. Collective efficacy will then be evaluated as a community practice theory guided by Jaccard and Jacoby's (2010) criteria for what constitutes a good theory. Chapter 2 will conclude with a critique of collective efficacy and provide conceptual and operational rationales for considering alternative models of collective efficacy.

Neighborhood Disorder

Neighborhood disorder refers to public behaviors that are threatening to residents such as public intoxication, and physical markers like garbage on the streets, graffiti, and abandoned buildings (Sampson, 2012). There are two main sub-types of disorder that comprise neighborhood disorder based on this definition: physical disorder and social disorder (Skogan, 1990). The impact of physical disorder is typically explained using broken windows theory (Wilson & Kelling, 1982). Broken windows theory states that indicators of physical disorder like broken windows, decaying buildings, and graffiti leads to a sense of powerlessness and withdrawal among residents, and signals to criminals that it is possible to conduct crime in the neighborhood with minimal risk of repercussions (Hinkle, 2009, 2013; Hinkle & Yang, 2014; Skogan, 1990). Social disorder refers to public behaviors like loitering, public intoxication, and dealing drugs (Hinkle, 2009, 2013; Hinkle & Yang, 2014; Sampson, 2012; Sampson & Raudenbush, 1999).

Conceptually, researchers often use the term disorder without making distinctions as to whether or not they are focusing on physical disorder, social disorder, or neighborhood disorder; which creates confusion about what the term, “Disorder” means (Kubrin, 2008). It is important to be clear about the type of disorder being studied because they have different implications for social work practice. For example, physical disorder can be addressed by redeveloping housing and cleaning up neighborhoods whereas social disorder can be addressed by providing after school programming for loitering youths.

Measuring Disorder. Typically, there are two methods of measuring disorder: objectively and subjectively (Hinkle, 2009, 2013; Hinkle & Yang, 2014; Sampson & Raudenbush, 2004; Taylor, 2001). Objective measures of disorder are based on the actual number of indicators of disorder in a neighborhood (e.g. the presence or absence of litter in the streets; Sampson & Raudenbush, 1999). Typically, objective measures of disorder use some form of systematic social observation (SSO) where researchers visit a neighborhood and take notes about indicators of disorder that they observe (Sampson & Raudenbush, 1999). One limitation of objective measures of disorder is that indicators of serious disorder (e.g. police raids and adults fighting) rarely occur while researchers are observing neighborhoods (Sampson & Raudenbush, 1999). A second limitation is that researchers may interpret something as an indicator of disorder, but residents may not

(Innes, 2004; Millie, 2008). This is a serious limitation of SSO because broken windows theory states that it is the *perception* of disorder that has a negative impact on residents (Zimbardo, 1969).

Subjective measures of disorder address some of the limitations of SSO. Typically collected by survey, subjective measures of disorder are based on resident perceptions of how much disorder exists in the neighborhood (Hinkle, 2009, 2013; Hinkle & Yang, 2014; Taylor, 2001). Conceptually, subjective measures of disorder reflect individuals' perception of disorder, which is at the core of broken windows theory. But research also suggests that objective and subjective measures of disorder are two different factors that impact neighborhoods (Hinkle & Yang, 2014; Sampson & Raudenbush, 1999, 2004; Skogan, 1990). Subjective measures of disorder are associated with higher levels of depression (Ross, 2000), physical health issues (Ross & Mirowsky, 2001), feelings of powerless and mistrust among residents (Ross et al., 2001), and lower levels of perceived safety (Hinkle & Yang, 2014) whereas objective measures of disorder are related to higher rates of crime and juvenile delinquency (Sampson et al., 1999; Sampson & Raudenbush 1999, 2004).

Historical Development of Collective Efficacy Theory

Social Disorganization. Collective efficacy is intellectually rooted in social disorganization theory (Busik & Grasmick, 1993; Sampson, 2004, 2006, 2012; Sampson et al., 1997; Sampson, Morenoff, & Earls, 1999). Social disorganization theory was developed by Shaw and McKay (1942, 1969) to explain why issues like neighborhood disorder are concentrated within certain areas of a city. Disorganized neighborhoods have a community structure that is generally characterized as being low socioeconomic status (SES; e.g. high rates of poverty, public assistance use, unemployment); with high rates of resident mobility (e.g. percentage of residents not living in the same residence five years prior), ethnic heterogeneity (e.g. racial diversity), single parent households, and urbanization (e.g. population density; Brenner, Bauermeister, & Zimmerman, 2011; Bruinsma, Pauwels, Weerman, & Bernasco, 2013; Hannon, 2005; Sampson, 1987; Sampson & Groves, 1989; Shaw & McKay, 1942, 1969). Studies suggest that social disorganization is associated with higher levels of neighborhood disorder because it interrupts social networks – defined as socially linked individuals and groups (Cleake & Howe, 2004; Wasserman & Faust, 1994) and reduces social capital within the neighborhood (Sampson & Groves, 1989; Shaw & McKay, 1942, 1969; Taylor, 2002; Veysey & Messner, 1999; Warner & Rountree, 1997).

Social Capital. Social capital can be defined as, "A social stock of trust and norms of reciprocity, which facilitates collective actions for mutual and individual benefits" (Ansari, 2013, p. 79). At the core of social capital is the idea that social networks generate resources that can be drawn upon to confront issues such as neighborhood disorder (Bellair, 1997; Bourdieu, 1985; Coleman, 1988, 1990; DeFilippis, 2001; Fischer, 2005; Portes, 1998; Portes & Sensenbrenner, 1993; Perkins, Florin, Rich, & Wandersman, 1990; Perkins, Wandersman, Rich, & Taylor, 1993; Putnam, 1993, 1995, 2000). Research suggests that there is a reciprocal relationship between social capital and neighborhood disorder. Signs of neighborhood disorder generate mistrust among neighbors (Ross & Mirowsky, 2009). Social capital is lower in these neighborhoods because trust is a critical component for the development of social capital (Putnam, 2000). Qualitative data also suggests that residents in neighborhoods with lower levels of social capital report higher levels of neighborhood disorder, suggesting a reciprocal relationship between the two (Packard, Callaway, Dorris, Suhr, 2013).

Social Cohesion. The aspect of social capital that is of particular interest to the conceptualization of collective efficacy is social cohesion (Baker, 1990; Buckner, 1988; Chavis & Wandersman, 1990; Coleman, 1988, 1990; Greenberg & Rohe, 1986; Lin, 1999, 2001; Portes, 2000; Schiff, 1992; Burt, 2000). Social cohesion is typically defined as the, "Extent of mutual trust, solidarity, and shared values among community residents," (Browning, Burrington, Leventhal, & Brooks-Gunn, 2008, p. 271). Although social cohesion is one dimension of social capital, Sampson and colleagues (1997) chose to examine social cohesion specifically because it focuses on shared expectations, neighborhood norms, and trust among neighbors (Ansari, 2013). Sampson and colleagues (1997) believe that social cohesion is a component of collective efficacy because residents are, "Unlikely to intervene in a neighborhood context in which the rules are unclear and people mistrust or fear one another" (p. 919).

Informal Social Control. Typically conceptualized as, a community's willingness to enforce social norms in the local area (Bursik & Grasmick, 1993; Sampson et al., 1997) informal social control is frequently cited as a neighborhood level predictor that is associated with lower levels of neighborhood disorder (Bursik & Grasmick, 1993; Elliot et al., 1996; Janowitz, 1976; Sampson, 2006; Sampson & Raudenbush, 2001; Sampson & Groves, 1989; Morenoff et al., 2001; Sampson, Morenoff, & Gannon-Rowley, 2002). In their book, Bursik and Grasmick (1993) use Hunter's (1985) conceptualization of social control to create a conceptual model of social control. According to Hunter (1985) there are three levels of social control: private, parochial, and public. The private level is the control generated between significant others (i.e. friends, family, spouse, etc.). The parochial level consists of informal community controls activated by community members through interpersonal interactions with individuals outside of the family and the presence of schools, churches, and local merchants. The public level depends on the connections between the community and outside agencies to access and leverage connections and services from sources outside their immediate neighborhood in order to achieve collective goals (Bursik & Grasmick, 1993).

Although originally viewed as three separate levels, researchers have since combined the private and parochial levels under the term informal social control because they exist outside of the criminal justice system, whereas the public level of social control is now referred to as formal social control (Carr, 2004; Clear, 2007; Clear, Rose, Waring & Skully, 2003; Kingston, Huizinga, Elliot, 2009; Rose & Clear, 2004; Velez, 2001). While there are researchers who study the effects of formal social control on communities (Clear, 2007; Clear, et al., 2003; Frost & Gross, 2012; Renauer, Cunningham, Feyerherm, O'Connor, Bellatty, 2006; Rose & Clear, 2004; Velez, 2001), collective efficacy research typically focuses on informal social control because it is both generated and enforced by community members (Sampson, 2006, 2012; Sampson et al., 1997; Sampson et al., 1999). According to Sampson (2006, 2012), informal social control is a bottom-up approach to enforcing norms whereas formal social control is top-down. This point is of particular importance to community practice, which focuses on utilizing the strengths and assets within a community to create change.

Collective Efficacy

In the original study of collective efficacy by Sampson and colleagues (1997), data were collected as part of the Project on Human Development in Chicago Neighborhoods (PHDCN; Felton, Brooks-Gunn, Raudenbush, & Sampson, 2005). Launched in the early 1990s, the PHDCN was designed to understand pathways of positive and negative neighborhood outcomes including juvenile delinquency, adult crime, and neighborhood disorder (Felton et al., 2005). Multiple methods of data collection were used including a representative survey of more than 8,000 Chicago residents in 1995, a follow up survey of 3,000 residents in 2002, and an SSO of more than 20,000 street segments (Felton et al., 2005; Sampson, 2012). SSO was one method used to measure neighborhood disorder. Researchers drove through street segments with while recording the area using video cameras. The videotapes were then coded for various types of disorder (Raudenbush & Sampson, 1999; Sampson, 2006, 2012). Neighborhood disorder was also measured through survey by asking residents how much of a problem certain signs of disorder were (e.g. litter/trash, graffiti, drinking in public, teenagers causing a disturbance; Sampson et al., 1997).

Operating under the assumption that social cohesion does not automatically lead to informal social control (Bellair, 1997; Bursik, 1999; Browning, Feinberg, & Dietz, 2004; Patillo-McCoy, 1999; Wilson, 2011), Sampson and colleagues (1997) tested the relationship between social cohesion and informal social control. Social cohesion was measured in the PHDCN with five Likert scale items: (1) people around here are willing to help their neighbors, (2) this is a close-knit neighborhood, (3) people in this neighborhood can be trusted, (4) people in this neighborhood generally don’t get along, and (5) people in this neighborhood do not share the same values. Scores were measured on a five-point scale ranging from 1 (strongly agree) to 5 (strongly disagree) and questions 4 and 5 were reverse coded (Felton et al., 2005). Informal social control was also measured using five items assessing how likely it is that neighbors would intervene if: (1) children were skipping school and hanging out on a street corner, (2) children were spray-painting graffiti on a local building, (3) children were showing disrespect to an adult, (4) a fight broke out in front of their house, and (5) the fire station closest to their home was threatened with budget cuts (Felton et al., 2005). Scores were measured on a five-point scale ranging from 1 (very likely) to 5 (very unlikely). Because social cohesion and informal social control were highly correlated (r = .80, p < .001), they were combined into one measure of collective efficacy (Sampson et al., 1997).

Although studies may modify the measures of social cohesion and informal social control developed by Sampson and colleagues (1997) slightly, the majority of collective efficacy studies measure collective efficacy using the PHDCN items (for reviews of studies see: Sampson et al., 2002; Sutherland et al., 2013). Examples of modifications to the collective efficacy items can be found in Bruinsma et al (2013) who changed question 5 of the informal social control scale to focus on a community center facing budget cuts. The Seattle Neighborhoods and Crime Survey (Matsueda, 2010) also made changes to the Sampson et al (1997) measure of collective efficacy. These changes will be described in Chapter 4.

Raudenbush and Sampson (1999) highlighted a need to determine the reliability and validity of community measures, otherwise known as the ecometric properties of community measures. Studies examining the ecometric properties of Sampson et al.'s (1997) measure of collective efficacy report consistent findings; namely that the trust and cohesion, and willingness to intervene items are reliable measures of social cohesion and informal social control (Bruinsma et al., 2013; Byrnes et al., 2011; Drakulich et al., 2012; Mazerolle et al., 2010; Kingston et al., 2009; Raudenbush & Sampson, 1999). Further, social cohesion and informal social control are two highly correlated factors, suggesting that they are two aspects of one construct – collective efficacy (Raudenbush & Sampson, 1999; Sampson et al., 1997).

The first study of collective efficacy using the PHDCN tested the relationship between collective efficacy and crime (Sampson et al., 1997). Their findings showed that a two standard deviation increase in collective efficacy was associated with a 26% reduction in the expected homicide rate (Sampson et al., 1997). Later research examined the impact that collective efficacy has on neighborhood disorder. Raudenbush and Sampson (1999) examined the correlations among social cohesion, informal social control, and neighborhood disorder (as measured by SSO). Social cohesion was negatively correlated with physical disorder ($r = -0.62$, $p < 0.05$) and social disorder ($r = -0.55$, $p < 0.05$). Informal social control was negatively correlated with physical disorder ($r = -0.55$, $p < 0.05$) and social disorder as well ($r = -0.56$, $p < .05$; Raudenbush & Sampson, 1999).

A later study by the same authors (Sampson & Raudenbush, 2004) attempted to replicate these findings using the 2002 follow up survey. In the words of Sampson (2012), their findings were, "Almost a complete replication" (p.138). White respondents reported higher levels of perceived social disorder compared to blacks ($b = -0.164$, $p < 0.05$), Latinos ($b = -0.07$, $p < 0.05$), and other non-white respondents ($b = -0.128$, $p < 0.05$). However, collective efficacy had a significant impact on neighborhood disorder in

1995 (Raudenbush & Sampson, 1999), but not in 2002 (Sampson & Raudenbush, 2004). Their findings suggest that community level outcomes may be driven by the racial meaning that individuals attribute to neighborhood disorder (Sampson & Raudenbush, 2004). The racial meaning of disorder can have very serious consequences like the over-policing of communities of color (Withrow, 2004).

Collective Efficacy and Neighborhood Disorder in Multiple Contexts

One noticeable source of bias of early collective efficacy studies is that the majority research was conducted in Chicago. Later studies would demonstrate that early findings were replicable elsewhere and not due to a “Chicago effect,” (Sampson, 2012). For example, Swatt, Varano, Uchida, and Solomon (2013) conducted a study across four neighborhoods in Miami-Dade County. The total sample was comprised of 524 individuals who were randomly sampled from active mailing addresses, and sample sizes within neighborhoods ranged from 103 to 155. Using multilevel modeling (MLM), researchers were able to demonstrate that collective efficacy was significantly ($p < 0.05$) associated with lower levels of neighborhood disorder in Brownsville (b = -0.249), Seminole Wayside Park (b = -0.160), East Little Havana (b = -0.285), but not Bunche Park (b = -0.095; Swatt et al., 2013). Reisig & Cancino (2004) collected data on a sample of 1,307 individuals across one county and two municipalities in Michigan. The researchers (Reisig and Cancino, 2004) conducted a multilevel Poisson regression, which showed that collective efficacy was a significant predictor of neighborhood disorder (b = -0.15, $p < .05$). Plank, Bradshaw and Young (2009) conducted a path analysis using OLS regression to examine a potential path where physical disorder predicts collective efficacy, which then predicts social disorder. Their sample was an anonymous survey that was administered to 6th-8th graders from 33 schools in a large Mid-Atlantic urban public school district. Their findings suggest that there was a negative association between collective efficacy, and both physical and social disorder (Plank et al., 2009). A dissertation (Hinkle, 2009) and accompanying article (Hinkle, 2013) used data from the San Bernardino Valley Broken Windows Experiment, which was a sample of 773 residents and business owners from San Bernardino Valley. The researcher conducted a path analysis that showed collective efficacy significantly predicted both social disorder (b = -0.41, $p < 0.001$) and physical disorder (b = -0.50, $p < 0.05$; Hinkle 2009, 2013). Taken together, these findings suggest that collective efficacy's impact on neighborhood disorder is generalizable to locations outside of Chicago (Sampson, 2012).

Community Structural Factors Impacting Collective Efficacy

Although researchers often place an emphasis on variables like collective efficacy that mediate the relationship between community structure (e.g. resident mobility, ethnic composition, poverty) and neighborhood disorder; Sampson, Morenoff, and Gannon-Rowley (2002) remind us that community structure is still important to study. Community structure can both have a direct impact on neighborhood disorder (Morenoff et al., 2001; South & Baumer, 2000; Peterson, Krivo, & Harris, 2000), and moderate the mediation effect of variables like collective efficacy (Sampson et al., 1999). For example, the effect of collective efficacy is stronger in neighborhoods with higher SES and greater resident stability (Burchfield & Silver, 2013; Sampson et al., 1999). Based on these findings, it should be expected that collective efficacy's impact on neighborhood disorder is weaker in less affluent neighborhoods, and neighborhoods with higher levels of resident mobility.

Another key factor that has an impact on collective efficacy is the racial composition of the neighborhood. Race has been shown to have an impact on the relationship between collective efficacy and neighborhood disorder. Specifically, whites perceived higher levels of neighborhood disorder compared to nonwhites (Sampson & Raudenbush, 2004). Research also suggests that ethnicity has an impact on collective efficacy. One study (Almeida, Kawatchi, Molnar, and Subramanian, 2009) found that Mexican-American neighborhoods had lower levels of social cohesion when compared to non-Latino, white neighborhoods in Chicago. Burchfield & Silver (2013) found that the mediation effect of collective efficacy is significantly weaker in Latino neighborhoods when compared to non-Latino neighborhoods in Los Angeles. These findings corroborate those of Galster and Santiago (2006) who found that low-income Latino families were less likely to report observing behaviors associated with neighborhood mechanisms like collective efficacy when compared to other low-income families. Therefore, it is important to consider ethnicity in community practice because the strength of collective efficacy's relationship with neighborhood disorder varies across neighborhoods with different ethnic compositions. It also suggests a need for practitioners to better understand the role that both race and ethnicity when attempting to develop collective efficacy in communities.

A study by Browning, Dietz, and Feinberg (2004) addresses an important question pertaining to the relationship between social networks and collective efficacy. Although many theorists agree that social networks are a community structural characteristic that is related to collective efficacy (Sampson et al., 1999), they differ in their thoughts about what type of social networks are best able to develop social cohesion and institute informal social control. One school of thought views large, dense networks as being optimal because close relationships among neighbors make it easier to identify individuals who are being deviant (Bourdieu, 1985; Coleman, 1988; 1990; Putnam, 1993, 1995, 2000). The other school of thought states that less dense networks matter in terms of generating collective efficacy because an individual does not need to be closely related to all of their neighbors in order to understand the shared expectations for acceptable behavior (Bellair, 1997; Granovetter, 1973; Kubrin & Weitzer, 2003; Patillo-McCoy, 1999; Sampson, 2006).

In order to test the role of social networks in generating collective efficacy, Browning and colleagues (2004) used the same PHDCN data as Sampson et al. (1997) to test the relationship between collective efficacy and crime across neighborhoods with low levels of social interaction and high levels of social interaction. Their findings suggest that collective efficacy has a greater impact in neighborhoods with lower levels of social interaction (Browning et al., 2004). Therefore, it is important to acknowledge the power that weak networks can have in terms of developing collective efficacy (Browning et al., 2004; Burchfield & Silver, 2013; Warner & Rountree, 1997).

Evaluating Collective Efficacy as a Community Practice Theory

Despite the amount of research on collective efficacy, it has not been evaluated as a community practice theory. However, Rosa & Tudge (2013) state that an important part of developing theory is to test theory, question its major concepts, and ensure that scholars base their work on an accurate reading of the theory as it currently exists. Jaccard and Jacoby (2010, p. 31-32) state that the following criteria are useful when evaluating a theory: utility, consensual validation, internal consistency, agreement with prior knowledge, testability, parsimony, consistency with prior theory, scope, creativity/novelty, and research generation. These criteria will be used to evaluate collective efficacy as a community practice theory in the following sections.

Utility. In order for theory to be useful it must be a guide to the world we experience and contribute to our understanding of the world (Jaccard & Jacoby, 2010). Collective efficacy has been demonstrated to have high utility because prior research has consistently shown that higher levels of collective efficacy are associated with lower levels of neighborhood disorder (Galster & Santiago, 2006; Maimon & Browning, 2010; Morenoff et al., 2001; O'Brien & Kauffman, 2013; Sampson & Morenoff, 2001; Sampson et al., 2002). The relationship between collective efficacy and neighborhood disorder has been supported in many different contexts (e.g. geographic and temporal), and while controlling for various community structural factors (e.g. concentrated disadvantage and residential stability; Morenoff et al., 2001; Sampson & Raudenbush, 1999). Therefore, collective efficacy theory is a useful guide for understanding the macro level factors that shape communities.

Consensual Validation. Consensual validation refers to the degree of consensus among the scientific community about the validity of a theory (Jaccard & Jacoby, 2010). In the case of consensual validation, validity refers to a general acceptance of a theory among the academic community (Jaccard & Jacoby, 2010). There is a great deal of consensus in the academic community about the validity of collective efficacy theory. There have been scholars to point out that cohesive neighborhoods do not automatically generate informal social control (Bellair & Browning, 2010), or that macro level predictors like collective efficacy have a weaker impact in certain neighborhood contexts

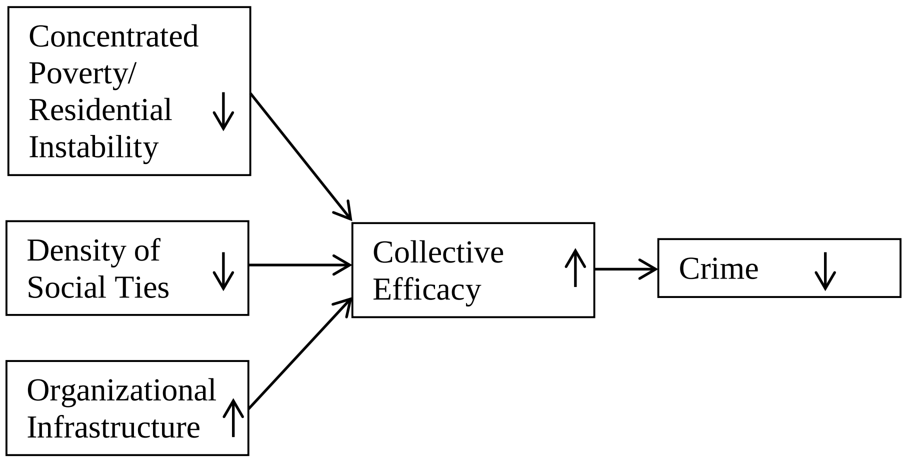
(Cagney et al., 2007). However, collective efficacy theory is generally supported by the academic community (Bellair & Browning, 2010; Boardman et al., 2001; Brisson & Altschul, 2011; Browning et al., 2013; Bruinsma et al., 2013; Foster & Brooks-Gunn, 2013; Galster & Santiago, 2006; Maimon & Browning, 2010; McDonell et al., 2015; O'Brien & Kauffman, 2013; Ohmer et al., 2010; Steenbeek & Hipp, 2011; Sutherland et al., 2013; Wickes et al., 2013).

Internal Consistency. For a theory to be internally consistent, statements within the theory must not contradict one another, nor lead to incompatible predictions (Jaccard & Jacoby, 2010; Reynolds, 1971). Sampson and colleagues (1997) state that social cohesion is important because residents are less likely to intervene in neighborhoods where the rules are unclear, and where the residents do not know one another. Because of this, neighborhoods with higher levels of social cohesion are more likely to informally monitor their neighborhood (Sampson et al., 1997). Typically, collective efficacy is viewed as a predictor of positive community outcomes (Browning et al., 2013; Bruinsma et al., 2013; Maimon & Browning, 2010; Morenoff et al., 2001; O'Brien & Kauffman, 2013; Sampson et al., 1997; Sampson et al., 1999). The statements that social cohesion is associated with higher levels of informal social control and collective efficacy is associated with positive neighborhood outcomes are internally consistent because they do not contradict one another.

Agreement with Prior Knowledge. A good theory should be in agreement with known data and facts (Jaccard & Jacoby, 2010). Collective efficacy builds upon prior knowledge of social capital and informal social control. Social capital theory states that there are resources that are associated with belonging to a social network (Bourdieu, 1985; Coleman, 1988, 1990; Putnam, 2000). Social control is an action that cannot exist without an "other" to informally monitor an individual (Bursik, 1999; Bursik & Grasmick, 1993). Collective efficacy examines how a particular aspect of social capital (social cohesion) relates to informal social control (Ansari, 2013; Sampson et al., 1997). Further, collective efficacy theory is a data driven theory because definitions of collective efficacy focus on how social cohesion is mobilized to bring about informal social control (Sampson et al., 1997). Because of this, there is a high degree of fit between the theory, prior knowledge, and data.

Testability. Good theories must also be subject to empirical validation (Jaccard & Jacoby, 2010). This means that a theory must be both testable and falsifiable (Reynolds, 1971). The breadth of research on collective efficacy suggest that it is testable (Bellair & Browning, 2010; Boardman et al., 2001; Brisson & Altschul, 2011; Browning et al., 2013; Bruinsma et al., 2013; Foster & Brooks-Gunn, 2013; Galster & Santiago, 2006; Maimon & Browning, 2010; McDonell et al., 2015; Morenoff et al., 2001; O'Brien & Kauffman, 2013; Ohmer et al., 2010; Sampson et al., 2002; Steenbeek & Hipp, 2011; Sutherland et al., 2013; Wickes et al., 2013). However, it is important to note that the theory is falsifiable as well. Research has suggested that combining social cohesion and informal social control may not accurately model collective efficacy empirically because cohesive neighborhoods do not always have higher levels of informal social control (Bellair & Browing, 2010; Brisson & Altschul, 2011; Wickes et al., 2013). Further, it is possible for the relationship between collective efficacy and neighborhood outcomes to not be supported.

Figure 1 – Current model of collective efficacy



Based on Sampson (2006)

Parsimony. A parsimonious theory is one that adequately explains a phenomenon with a minimum number of constructs and principles (Jaccard & Jacoby, 2010). Figure 1 depicts a commonly used model of collective efficacy, and the majority of research operationalizes collective efficacy using items similar to Sampson and colleagues (1997; Bellair & Browning, 2010; Boardman et al., 2001; Brisson & Altschul, 2011; Browning et al., 2013; Bruinsma et al., 2013; Foster & Brooks-Gunn, 2013; Galster & Santiago, 2006; Maimon & Browning, 2010; McDonell et al., 2015; Morenoff et al., 2001; O'Brien & Kauffman, 2013; Ohmer et al., 2010; Sampson et al., 2002; Steenbeek & Hipp, 2011; Sutherland et al., 2013; Wickes et al., 2013). This model is parsimonious because it explains a macro level process that is associated with complex social issues such as neighborhood disorder and other negative outcomes, but it has very few concepts. Combining measures of social cohesion and informal social control helps capture the two components of collective efficacy while reducing the number of constructs in the model.

Consistent with Prior Theory. A good theory is also consistent with other theories that have been accepted among the scientific community (Jaccard & Jacoby, 2010). Collective efficacy theory is consistent with prior theory. Collective efficacy is intellectually rooted in social disorganization theory, which states that neighborhood networks are disrupted in disorganized neighborhoods, which in turn leads to negative outcomes like neighborhood disorder (Busik & Grasmick, 1993; Sampson, 2004, 2006, 2012; Sampson et al., 1997; Sampson, Morenoff, & Earls, 1999). Social cohesion is a necessary precondition for informal social control (Ansari, 2013; Bursik, 1986). Because of this, Sampson and colleagues (1997) tested the relationship between social cohesion and informal social control, and developed collective efficacy. They also tested the relationship between collective efficacy and crime (Sampson et al., 1997).

Scope. According to Jaccard & Jacoby (2010), the greater the range of a theory, the better it may be. Theories of a greater range are able to explain more outcomes (Jaccard & Jacoby, 2010). It can be argued that collective efficacy theory is broad in scope because it is associated with multiple outcomes such as mental health (Ahern & Galea, 2011; Browning, Soller, Gardner, & Brooks-Gunn, 2013; Ursano et al., 2014), physical health (Small, 2009), intimate partner violence (Browning, 2002), and underage drinking (Maimon & Browning, 2012). However, scientists are able to narrow the scope of the theory to answer research questions pertaining to outcomes of interest. In this regard, the scope of collective efficacy theory is a strength because it is broad enough to predict multiple outcomes, but can also be narrowed to address specific issues and topics of interest.

Creativity/Novelty. A novel theory is one that explains an interesting phenomenon in a new way (Jaccard & Jacoby, 2010). Collective efficacy is a novel theory because it builds the work of two very large theories: social capital and informal social control (Sampson et al., 1997; Sampson et al., 1999). Sampson and colleagues (1997) identify social cohesion as a key resource for communities. However, social cohesion needs to be activated in order to be meaningful (Sampson 2004, 2012). Social cohesion is activated in the form of informal social control. Further, collective efficacy is a predictor multiple outcomes that are not easily solved such as neighborhood disorder (Raudenbush & Sampson, 1999; Swatt et al., 2013) and crime (Sampson et al., 1997, Morenoff et al., 2001). Because of this, collective efficacy can be considered a novel theory that provides insight into how to improve neighborhood outcomes.

Research Generation. A good theory will also generate a great deal of scientific research (Jaccard & Jacoby, 2010). Collective efficacy theory has generated a large amount of research both in the United States and abroad. For example, the original study of collective efficacy (Sampson et al., 1997) has been cited by over 7,000 studies according to Google Scholar. The theory has also been explored in multiple countries including Australia (Mazerolle et al., 2010), Canada (Thompson, Bucerius, & Luguya, 2013), China (Zhang, Messner, and Liu, 2007), Sweden (Sampson & Wikström, 2008; Wikström & Dolmen, 2001), the United Kingdom (Steptoe & Feldman, 2001; Wikström, Oberwittler, Treiber, and Hardie, 2012), the Netherlands (Bruinsma et al., 2013), Brazil (Villareal & Silva, 2006), and Thailand (Byrnes et al., 2011).

Critiquing Collective Efficacy

Brinberg & McGrath (1985) state that criteria for what constitutes a good theory can conflict with one another. In terms of evaluating collective efficacy as a community practice theory, the criteria of parsimony and utility appear to be at odds with one another. Collective efficacy theory is both parsimonious and useful. However, it is important to consider what collective efficacy is useful for. Collective efficacy is a theory that was developed to explain the relationship between community structure and crime (Sampson et al., 1997; Sampson et al., 1999). To that end, parsimony is a strength of collective efficacy because it is able to model the relationship between social cohesion and informal social control with one construct. However, combining social cohesion and informal social control presents a challenge because research suggests that cohesive neighborhoods do not automatically institute informal social control (Armstrong et al., 2010; Bellair & Browning, 2010; Brisson & Altschul, 2011; Wickes et al., 2013). Because of this, it is reasonable to suggest that there are factors mediating or moderating the relationship between social cohesion and informal social control. Therefore, social work researchers need to understand the process by which social cohesion is mobilized to bring about actions like informal social control in order to facilitate collective action in communities.

Modeling Collective Efficacy. The majority of research on collective efficacy combines social cohesion and informal social control into one concept (collective efficacy; Bellair & Browning, 2010; Boardman et al., 2001; Brisson & Altschul, 2011; Browning et al., 2013; Bruinsma et al., 2013; Foster & Brooks-Gunn, 2013; Galster & Santiago, 2006; Maimon & Browning, 2010; McDonell et al., 2015; Morenoff et al., 2001; O’Brien & Kauffman, 2013; Ohmer et al., 2010; Sampson et al., 2002; Steenbeek

& Hipp, 2011; Sutherland et al., 2013; Wickes et al., 2013), However, Sampson (2013, p. 26) frames collective efficacy as a process that focuses on the, "*Activation* and *content* of social ties" (italics original). The first step in more fully understanding the process of collective efficacy is separating social cohesion from informal social control. Scholars have made conceptual and empirical arguments to separate the two constructs (Bellair & Browning, 2010; Brisson & Altschul, 2011; Bursik, 1999; Wickes et al., 2013). These arguments will be described in the following paragraphs.

High correlations between factors may be evidence to support combining measures into one construct, but one also must consider the importance of theory when making such a decision (Pett, Lackey, Sullivan, 2003). Conceptually, social cohesion is thought of as a prerequisite for informal social control, but the concepts are not one and the same (Bursik, 1999; Paskevich, Brawley, Dorsch, & Widmeyer, 1999). Social cohesion is a resource that can be drawn upon to by communities to accomplish tasks like informal social control (Bursik, 1999; Bourdieu, 1985; Coleman 1988, 1990; Putnam, 2000). Informal social control however, is an action (Bursik & Grasmick, 1993). These concepts should be highly correlated because cohesive neighborhoods are more likely to institute informal social control (Sampson et al., 1997), but this does not make the resource for action (social cohesion) the same as the action itself (informal social control).

Empirical research has tested for statistical differences among these concepts as well. Although many studies cite Cronbach's alpha to support the unidimensionality of collective efficacy, it is important to state that internal consistency is not an adequate test of the dimensionality of items (Cortina, 1993). Because of this, Brisson and Altschul

(2011) conducted a multilevel confirmatory factor analysis (MLCFA) on collective efficacy items using data from the Annie E. Casey Foundation's Making Connections study. Making Connections is an evaluation of comprehensive community initiatives that target low-income neighborhoods in 10 cities: Denver, Colorado; Des Moines, Iowa; Harford, Connecticut; Indianapolis, Indiana; Louisville, Kentucky; Milwaukee, Wisconsin; Oakland, California; Providence, Rhode Island; San Antonio, Texas; and Seattle Washington (Coulton, Theodos, & Turner, 2009). The data in Brisson and Altschul's (2011) study consisted of 7,496 people across 418 Census Block Groups. The results from their MLCFA suggested that combining social cohesion and informal social control did not demonstrate good model fit (CFI = 0.856; RMSEA = 0.081; SRMR within = 0.042, SRMR between = 0.091) even though the internal consistency of the items was adequate ($\alpha = 0.809$; Brisson & Altschul, 2011). The two factor solution fit the data better (CFI = 0.999; SRMR within = 0.002, SRMR between = 0.053) and the two concepts were positively correlated ($r = 0.750$, $p < 0.001$; Brisson & Altschul, 2011)

Another study by Wickes and colleagues (2013) attempted to examine the relationships among social cohesion and informal social control. Their study used data from the Australian Community Capacity Study (ACCS). The ACCS is a longitudinal survey of Australian residents that is collected though random digit dialing in the Brisbane Statistical Division in Queensland, Australia (Wickes et al., 2013). The study sample consisted of 4,093 individuals across 148 neighborhoods (Wickes et al., 2013). Similar to Brisson and Altschul (2011), combining social cohesion and informal social control into one concept did not adequately fit the data (CFI = 0.88, TLI = 0.85, RMSEA

= .064; Wickes et al., 2013). Separating the concepts demonstrated an improvement in model fit (CFI = 0.95, TLI = 0.93, RMSEA = .045; Wickes et al., 2013).

Armstrong, Katz and Schnebly (2015) used 2002 data from a random sample of 800 residents in Mesa, Arizona. A principal components analysis of collective efficacy presented mixed findings pertaining to the factor structure of collective efficacy. Although eigenvalues suggested that a two-factor model fit the data best, factor loadings provided support for a one factor model. Because of this finding, the authors conducted four regression models predicting violent crime. Model 1 combined social cohesion and informal social control into collective efficacy, model 2 entered social cohesion, but not informal social control, model 3 entered informal social control, but not social cohesion, and model 4 entered social cohesion and informal social control independently. When social cohesion and informal social control were independent predictors in the regression social cohesion was a significant predictor of lower violent crime ($\beta = -0.325$, $p < 0.01$) whereas informal social control was not ($\beta = -0.098$, $p > 0.05$; Armstrong et al., 2015). Taken together, the findings of Armstrong and colleagues (2015) suggest that social cohesion and informal social control are two concepts.

Conclusion – Chapter 2

This literature review demonstrates that collective efficacy has generated a considerable amount of research, and its relationship with neighborhood disorder has been supported in multiple contexts. The evaluation of collective efficacy as a community practice theory suggests that it is a strong theory based on many of the criteria proposed by Jaccard and Jacoby (2010). However, the decision to combine social cohesion and informal social control limits our ability to understand how social cohesion is activated in communities. As stated in this chapter, there may be factors that mediate or moderate the relationship between social cohesion and informal social control. These variables cannot be studied if social cohesion and informal social control are combined into one concept. The next chapter will introduce a new concept called mutual efficacy that is a possible mediator of the relationship between social cohesion and informal social control.

Chapter 3 – Mutual Efficacy

The primary contribution of this study is the development of a new concept called "mutual efficacy[1]." I define mutual efficacy as, "Community members' beliefs that collective action will be successful at attaining group goals." Mutual efficacy can advance social work practice and research by making an implicit part of collective efficacy more explicit. A second contribution of this study is exploring mutual efficacy's role as a mediator of the relationship between social cohesion and informal social control.

This chapter will begin by describing the similarities and differences between the conceptual and operational definitions of collective efficacy proposed by Bandura (1997), and Sampson (2012). The chapter will then conceptualize mutual efficacy and provide a rationale for labeling the concept "mutual efficacy." The chapter will then model mutual efficacy as a variable that mediates the relationship between social cohesion and informal social control. Chapter 3 will conclude with a discussion of how to operationalize mutual efficacy.

Collective Efficacy: Sampson and Bandura

In the community practice literature, collective efficacy is typically viewed as a community level construct developed by Sampson and colleagues (1997) that focuses on the content and activation of social ties (Sampson, 2013). A common definition of collective efficacy is, "Shared beliefs in neighbors' conjoint capability for action to achieve an intended effect and hence, an active sense of engagement on the part of residents" (Morenoff et al., 2001, p. 521). Albert Bandura (1997, 2006) is another well-

[1]The term "mutual efficacy" was developed in a class discussion among Dr. Mark Joseph, students, and myself in the Mandel School class SASS 534 – Theoretical Contexts Shaping Community Practice (Fall, 2015).

known theorist who primarily studies self-efficacy, which focuses on an individual's belief that their actions can be successful. However, Bandura also writes about collective efficacy, which he defines 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 (p. 477)." Both Bandura (1997) and Sampson (2006) state that that efficacy, regardless of whether it is being conceptualized on the individual or group level, focuses on the *belief* that actions will be successful. However, there are key differences between theorists in terms of the operationalization of collective efficacy.

As stated in Chapter 2, the measure of collective efficacy developed by Sampson and colleagues (1997) reflects the levels of social cohesion and informal social control. Although many authors state that the items can be combined into one scale because the internal consistency of the combined items is acceptable (Boardman et al., 2001; Browning et al., 2013; Bruinsma et al., 2013; Foster & Brooks-Gunn, 2013; Galster & Santiago, 2006; Maimon & Browning, 2010; McDonell et al., 2015; Morenoff et al., 2001; O'Brien & Kauffman, 2013; Ohmer et al., 2010; Sampson et al., 2002; Steenbeek & Hipp, 2011), internal consistency is not evidence that a set of items are unidimensional (Cortina, 1993). More recent research using confirmatory factor analysis suggests that a two-factor solution fits the data better despite the acceptable internal consistency of the combined items (Brisson & Altschul, 2011; Wickes et al., 2013). For example, Brisson and Altschul (2011) found that the alpha coefficient of the combined collective efficacy items was 0.809 even though it did not fit the data well. Further, the two-factor solution allows researchers to study the impact that social cohesion has on multiple actions

(Wickes et al., 2013) as well as the unique impact that social cohesion and informal social control have on outcomes (Armstrong et al., 2015).

Because Bandura (1997, 2006) views collective efficacy as its own construct, it can be measured by a set of items that are unique from social cohesion and informal social control. This has been done to a limited extent in the literature. For example, Goddard, Hoy, and Hoy (2000) developed a measure of teacher collective efficacy that focuses on the belief that teachers within the same school can work together to achieve goals. Items on this scale include the degree to which teachers agree with statements such as: teachers in this school think that there are some students that no one can teach, and teachers in this school are skilled in various methods of teaching. Benight (2004) developed a scale that measures the collective efficacy of a community's ability to respond to a natural disaster. Items on this scale pertain to how well the community will be able to handle situations such as quickly coordinating community wide actions and deal with emotional responses that are part of a disaster. See Appendix E for the collective efficacy measures developed by Sampson and colleagues (1997), Goddard et al. (2000) and Benight (2004).

To the knowledge of this author, no general measure reflecting community members' beliefs that collective action will be successful has been developed to date. The measure developed by Goddard and colleagues (2000) focuses exclusively on teachers, and the Benight (2004) measure of collective efficacy is task specific because it only focuses on a community's response to a natural disaster. A possible reason why measures like the two developed by Goddard et al. (2000) and Benight (2004) are not commonly used in the community practice literature is that researchers assume that the measure of collective efficacy developed by Sampson and colleagues (1997) reflects residents' perceptions that collective action will be successful. A noticeable difference between the Sampson et al. measure (1997) and the measures developed by Goddard and colleagues (2000) and Benight (2004) is that the Sampson et al. (1997) measure does not reflect whether or not a resident believes that action will be successful. Rather, the measure developed by Sampson and colleagues (1997) focuses on perceived social cohesion and the likelihood that neighbors will intervene to prevent neighborhood problems. To address this limitation in prior collective efficacy research, the remainder of this chapter will focus on the conceptual and operational development of mutual efficacy and provide the theoretical justification to include mutual efficacy in our current model of collective efficacy (Appendix C).

Conceptualizing Mutual Efficacy

As stated in the introduction to this chapter, one of the significant contributions of this study to advance both collective efficacy research and practice is the development of a new concept called "mutual efficacy." Mutual efficacy is defined as, "Community members' beliefs that collective action will be successful at attaining group goals." Although prior collective efficacy research implies that residents' perceptions that collective action will be successful is part of collective efficacy (Morenoff et al., 2001; Sampson 2004, 2006, 2012; Sampson et al., 1997), this study will make this belief more explicit. Conceptually, mutual efficacy is rooted in the work of Sampson (2012) and Bandura (1997) because it focuses on the belief that collective action will be successful. Mutual efficacy is different from Sampson's work on collective efficacy however, because mutual efficacy is a construct that mediates the relationship between social cohesion and informal social control in our current model of collective efficacy. The rationale behind modeling collective efficacy in this way will be described later in the chapter.

Although the definition of mutual efficacy is very similar to Bandura's (1997) definition of collective efficacy, the name "mutual efficacy" has a very specific connotation. The decision to coin the term "mutual efficacy" was made for two primary reasons. The first reason is to prevent conceptual confusion. Placing a concept named collective efficacy in a model of collective efficacy is awkward because it would require authors to repeatedly distinguish whether or not they are referring to the model or the concept. The second reason is that it provides a particular frame through which to view communities. The word "mutual" is borrowed from the term "mutual help groups." Typically discussed in literature that focuses on empowerment, mutual help groups are groups that "encourage people to feel and use their own strength to resolve problems" (Suler, 1984, p.30), which emphasizes the importance of empowering groups to solve issues using their own strengths and assets (Humphreys & Noke, 1997; Maton, 2008; Suler, 1984).

Researchers typically focus on the way in which organizations like Alcoholics Anonymous create mutual help groups (Humphreys & Noke, 1997; Maton, 2008; Suler, 1984). However, communities can be thought of as a mutual help group that is developed by community members; which includes both individuals and organizations. Viewing communities as both individuals and organizations is consistent with informal social control because it combines the private and parochial levels of informal social control. As stated in Chapter 2, the private level relies on relationships with significant others (i.e. friends, family, spouse), and the parochial level focuses on individuals that are not significant others, and organizations like schools, churches, and local merchants. Combining individuals and organizations in the definition of community is also consistent with our conceptualization of social cohesion because organizations are community stakeholders. For this reason, Felton and colleagues (2005) surveyed community organizations about their perceptions of social cohesion as part of the PHDCN study. Further, it underscores the role that neighborhood organizations like CDCs can play in fostering social cohesion, mutual efficacy, and informal social control (Sampson, 2012). Viewing communities as a mutual help group is also consistent with community practice, which focuses on developing the strengths of a community and allowing the community to co-create solutions to issues (Freire, 1993; Green 2006; Kretzman & McKnight, 1996; Matton, 2008; Watts, Williams, & Jagers, 2003).

An interesting implication of viewing communities as a mutual help group is that it ties collective efficacy theory to a process that is closely related to, but unique from collective efficacy – empowerment (Wandersman & Florin, 2000). Empowerment is defined by Maton (2008) as, "A group-based, participatory developmental process through which marginalized or oppressed individuals and groups gain greater control over their lives and environment, acquire valued resources and basic rights, and achieve important life goals and reduced societal marginalization" (p. 5). Although the belief that actions will be successful is a component of empowerment, mutual efficacy can still be thought of efficacy. This is because empowerment includes factors like motivation, skills, and meaningful roles (Maton, 2008) whereas mutual efficacy focuses exclusively on the belief that collective actions will be successful. Although our current understanding of collective efficacy implies that community members are engaged in the process of addressing neighborhood issues through informal social control, linking mutual efficacy to mutual help groups and empowerment makes the role of ongoing community engagement and empowerment more explicit.

Another benefit of mutual efficacy is that it can be applied to multiple definitions of community. For example, Leventhal, Brooks-Gunn, and Kamerman (1997) list three ways communities can be defined: place, space, and face. Defining communities by place bases the definition of communities on geographical borders (e.g. Census Tracts, or the street segments between two major roads). Defining communities as space refers to the built environment (e.g. buildings and open spaces). These communities include individuals that attend a particular school or use the local park. Although these examples have a geographical element to them such as living within the same school district as the school, the definition of the community is based on the building itself. Communities of face are defined by a sense of identity that is not tied to a particular geography or building such as being a member of the LGBTQ community, or the black lives matter movement. Many studies of collective efficacy define communities by place because they focus on neighborhoods (Armstrong et al., 2010; Cohen et al., 2006; Galster & Santiago, 2006; Morenoff et al., 2001; O'Brien & Kauffman, 2013; Sampson et al., 1997; Sampson et al., 1999; Sampson, 2012). However, mutual efficacy makes the flexibility of collective efficacy in terms of its applicability to other types of communities more explicit.

The inability to use collective efficacy as the label for community members' beliefs that collective action will be successful at attaining group goals may be a mixed blessing. Although the definitions of mutual efficacy and collective efficacy are nearly identical, the implications of the word, "mutual" are profound. It creates a link between collective efficacy and empowerment in a manner that is consistent with both constructs. Mutual efficacy provides an explicit frame through which collective efficacy theorists can view communities. Further, mutual efficacy makes the fact that collective efficacy can apply to multiple definitions of community, and that community change is a long-term process that requires continual community engagement more explicit.

Modeling Mutual Efficacy in Collective Efficacy Theory

A second contribution of this study is testing whether or not the relationship between social cohesion and informal social control is mediated by another variable. In the case of this study, the mediator of interest is mutual efficacy. Appendix A illustrates this model. This model is theoretically consistent with prior work of collective efficacy. Sampson and colleagues (1997) state that residents are more likely to informally monitor their neighborhoods if residents know and trust one another. However, recent research suggests separating social cohesion and informal social control because social cohesion does not always correspond with higher levels of informal social control (Bellair & Browning, 2010; Brisson & Altschul, 2011; Wickes et al., 2013). A possible explanation for these findings is that a variable is mediating the relationship between social cohesion and informal social control (Jaccard & Jacoby, 2010). This study proposes that mutual efficacy is a possible mediator of the relationship between social cohesion and informal social control.

Mutual efficacy is expected to be predicted by social cohesion because cohesive communities have a shared understanding of the community including expectations for acceptable behavior, values, and a sense of trust among members (Sampson et al., 1997). Social cohesion is an important precondition for developing consensus within groups (Bandura, 1997). Consensus refers to the ability of groups to agree on a course of action (Bandura, 1997). Consensus is associated with stronger beliefs that collective action can be successful because it demonstrates that the group can achieve goals like agreeing on issues (Bandura, 1997). Therefore, cohesive communities are expected to have higher levels of mutual efficacy because they are more likely to have greater consensus on things like expectations for acceptable behavior and community values. Mutual efficacy is expected to predict informal social control because Bandura (1997) and Sampson (2012) both acknowledge that groups who believe that actions will be successful will be more likely to act. Applying this logic to mutual efficacy, which is a concept that focuses on community members' perceptions that collective action will be successful; it is expected that higher levels of mutual efficacy will be associated with higher levels of informal social control.

To put the model in Appendix A into simple terms, social cohesion states that, "We feel that we are part of a community," and mutual efficacy states that, "we believe that if we work together we can achieve our goals." Community members who believe that their actions will be successful are more likely to act by instituting informal social control. Although this description is linear in nature (social cohesion leading to mutual efficacy and then informal social control), there are likely to be reciprocal relationships that exist among these constructs. Mutual efficacy can impact social cohesion because residents who believe that collective action can be successful may also be more likely to recruit other community members for their input and/or participation in the community change process. Further, communities can either implicitly or explicitly develop goals like the reduction of neighborhood disorder (Hardcastle, Powers, & Wencour, 2004). The process of identifying and agreeing upon goals can increase social cohesion. Successful community action can build momentum for the change process (Fook, 2002; Mezirow, 2000; Mezirow & Taylor, 2009). Because of this, successful actions like cleaning up dumping sites in vacant lots can not only lower levels of neighborhood disorder, but it can also build mutual efficacy (Nagel, 1990). Further, individuals that are active in the community are more likely to meet other community members (Bellair, 1997). Because of this increase in social interaction, informal social control may increase social cohesion as well.

Measuring Mutual Efficacy

An important question is how to measure mutual efficacy as a concept that is independent of both social cohesion and informal social control. Although the conceptualization of mutual efficacy is rooted in the work of Sampson (2012) and Bandura (1997), the measurement of mutual efficacy draws heavily from the work of Bandura (1997, 2006). This is due to the fact that the measure of collective efficacy developed by Sampson and colleagues (1997) is meant to reflect social cohesion and informal social control rather than community members' beliefs that collective action will be successful. The work of Bandura (1997, 2006) however, explicitly focuses on the belief that collective action will be successful.

As stated by Sampson (2012) and Bandura (1997) efficacy is concerned with the perception that actions will be successful. Bandura (2006) states that measures of efficacy, whether measured at the individual or collective levels are, "Concerned with perceived capability. The items should be phrased in terms of *can do* rather than *will do* (p. 308) (italics original)." Measures of self-efficacy focus on the perceived capabilities of the individual (e.g. I believe that *I* will be successful). Measures of collective efficacy focus on the capability of groups to achieve goals (e.g. I believe that *we* will be successful; Bandura, 1997; 2006). Therefore, measuring collective efficacy is more than a summation of scores on measures focusing on the individual and is more concerned with the belief in the effectiveness of a group (Bandura, 1997, 2006).

Measures mutual efficacy should focus on the beliefs in the effectiveness of the community. This means that problems discussed in the items should pertain to the community (e.g. I do not believe the problems of *this community* can be solved). Items should also examine the community as a whole, rather than the members that make up the community. For example, asking respondents to evaluate how well, "*People in this community* can work together to solve its problems," focuses on the individuals within the community whereas asking respondents to evaluate how well, "*This community* can work together to solve its problems," focuses on the collective. The wording in the latter item also implies that the respondent is part of the community of interest. Acknowledging that the respondent is part of the community of interest is a strength because it allows the respondent to share ownership of the community's level of mutual efficacy. However, respondents may be more likely to respond in a positive manner to mutual efficacy items because they share ownership of mutual efficacy with other community members. Though this may be considered a form of social desirability bias (DeVellis, 2010), it also fits the conceptual framework in terms of the relationship between social cohesion and mutual efficacy because individuals that feel like they belong to a community are expected to have higher levels of mutual efficacy.

A pool of items that can potentially be used for a measure of mutual efficacy can be found in Appendix F. Based on the guidelines above, these items reflect community members' perceptions that collective action can be successful at achieving group goals. A marker item that reflects this is, "This community can solve the problems it faces if we work together." Other items focus generally on whether or not problems facing the community can be solved, the community's ability to act collectively, and the community's ability to reach consensus on the problems facing the community. Items are measured using a five point Likert scale in order to maintain consistency with the measures of social cohesion and informal social control developed by Sampson and colleagues (1997). Although research is needed to determine which items from the pool should be included in a mutual efficacy scale, these items can serve as a useful starting point. Ideally, the mutual efficacy scale will be made up of four to five items in order to maintain consistency with the Sampson et al (1997) measures of social cohesion and informal social control (DeVellis, 2012).

Conclusion – Chapter 3

Bandura (1997) and Sampson (2012) both consider group members' perceptions that collective actions will be successful to be central to collective efficacy. Although the definition of mutual efficacy is similar to the definition of collective efficacy proposed by Bandura (1997) and Sampson (2012), there are important differences to consider. The name "mutual efficacy" draws from literature pertaining to empowerment, which frames communities as a group that encourages its members to identify their strengths and use them solve issues. It also places a focus on continually engaging the community in a long-term change process. Mutual efficacy is also framed as a mediator of the relationship between social cohesion and informal social control. However, it is expected that there will be reciprocal relationships among these variables. The following chapter will outline the methods used to test the model in Appendix B.

Chapter 4 – Methods

Chapter 4 begins with a description of the Seattle Neighborhoods and Crime Survey including the justification for using the dataset and the sampling procedures used by the original researcher (Matsueda, 2010). The chapter will then describe the measures used in the study in the following sections: dependent variables, focal predictors, and individual level variables. The analysis plan will then be described including the handling the missing of data, univariate statistics, determining the internal consistency of measures, data screening, checking the assumptions of statistical tests, and a description of the primary statistical methods to be used in the study: exploratory factor analysis, and structural equation modeling; which includes multilevel confirmatory factor analysis and a structural model.

Data Source and Sampling

Data for this study are drawn from the Seattle Neighborhoods and Crime Survey, 2002-2003 (SNCS). Conducted between 2002 and 2003, the SNCS was designed by researchers at the University of Washington to test multilevel theories of neighborhood social organization and criminal violence (Matsueda, 2010). The data are multilevel because individual respondents have a randomly generated identifier that corresponds to the Census Tract that the respondent lives in (Matsueda, 2010). This is important because social cohesion, mutual efficacy, and informal social control are all neighborhood level constructs (Sampson, 2012). The SNCS allows for individual responses to be aggregated by Census Tract and obtain neighborhood averages on each of the variables. The SNCS is also useful for this study because it includes two measures that tap into mutual efficacy: (1) how effective would small groups of neighbors be at resolving major problems around your neighborhood, and (2) how effective would organized neighborhood associations or community clubs be at resolving major problems around your neighborhood?

The SNCS sample was recruited by a sampling firm in Philadelphia using a constantly updated compilation of white pages as the sampling frame. The sampling firm randomly selected two block groups from each of Seattle's 123 census tracts (Matsueda, 2010). Roughly nine households per block group were randomly selected to be surveyed using a computer-assisted telephone interview (CATI). Surveys were conducted by the Social and Behavioral Research Institute at California State University, San Marcos (Matsueda, 2010). The researchers implemented three different sampling strategies as part of the overall study: (1) a random sample of households within the 123 Census Tracts, (2) an ethnic oversample, which obtained a disproportionate number of households with a high percentage of racial and ethnic minorities, and (3) a sample that replicates the sample used by Terrance Miethe in his 1990 Victimization Survey (Testing Theories of Criminality and Victimization in Seattle, 1960-1990; Matsueda, 2010). Because the Meithe replication sample uses different census boundaries than the other samples it will not be used in the study.

The random sample resulted in 2,220 households (Matsueda, 2010). The ethnic oversample obtained a disproportionate number of racial and ethnic minorities. To do this, the researchers identified 141 block groups with high concentrations of racial and ethnic minorities in Seattle, and then selected 558 census blocks from these block groups. Two households per block were randomly selected to complete the survey. The ethnic oversample resulted in 1,145 households. When combined with the random sample, the total sample for this study is 3,365. Despite conducting an ethnic oversample, the SNCS data are not weighted (Matsueda, 2010). Matsueda (2010), reports two measures of response rates for the SNCS: the American Association for Public Opinion Research (AAPOR) cooperation rate is, “The proportion of all cases of all eligible units ever contacted” (AAPOR, 2008; p. 4), and the Council of American Survey Research Organizations (CASRO) response rate, which is, “The number of complete interviews with reporting units divided by the number of eligible reporting units in the sample” (AAPOR, 2008; p. 4). The AAPOR cooperation rate for this study was over 97 percent and the CASRO response rate was over 51 percent (Matsueda, 2010).

The data underwent a confidentiality review by the Inter-University Consortium for Political and Science Research (ICPSR). The ICPSR also made the following changes to the data: standardized missing values, created online analysis versions with question text, performed recodes and/or calculated derived variables, and checked for undocumented or out of range codes (Matsueda, 2010).

Measures

This study will incorporate measures for both the individuals responding to the survey and aggregate individual level measures to obtain average scores for the neighborhoods in which the respondents live. Neighborhood was operationalized as Census Tract in the SNCS (Matsueda, 2010). Although Census Tracts may not reflect residents’ perceptions of what constitutes their neighborhood (Bursik & Grasmick, 1993; Coulton, Korban, Chan & Su, 2001), prior research suggests that Census Tracts are a close approximation of Seattle neighborhoods (Drakulich et al., 2012; Matsueda, 2010). Further, Census Tracts are practical approximations of neighborhoods that are used by most researchers (Coulton et al., 2001; Fostor & Hipp, 2011; Raudenbush & Sampson, 1999). The measures section will discuss the variables to be used in the study in the following sections: dependent variables, focal predictors, and individual level measures.

Dependent Variable

Neighborhood Disorder. Neighborhood disorder will be measured by combining five items that reflect the severity of problems in the neighborhood (e.g. abandoned houses, and spray painted graffiti on buildings and streets). Response options on each item range from 1 (not a problem) to 3 (a big problem). Scores on the resultant neighborhood disorder scale can range from 5 to 15 with higher scores reflecting greater levels of neighborhood disorder.

Focal Predictors

Social Cohesion. Social cohesion will be operationalized using items based on the social cohesion measure developed by Sampson and colleagues (Sampson et al., 1997). This measure assesses residents' agreement with the following statements: (1) you can count on adults in this neighborhood to watch out that children are safe and don't get into trouble, (2) people in this neighborhood can be trusted, (3) adults in this neighborhood know who the local children are, and (4) people around here are willing to help their neighbors. Response options range from 1 (strongly agree) to 4 (strongly disagree).

Informal Social Control. Informal social control was operationalized using items based on the informal social control measure developed by Sampson & Colleagues (Sampson et al., 1997). This measure assesses a residents' perceptions of the likelihood that neighbors would intervene during the following situations: (1) if a group of neighborhood children were skipping school and hanging out on a street corner, (2) if some children were spray-painting graffiti on a local building, (3) if a child was disrespecting an adult, and (4) if children were fighting out in the street. Response options range from 1 (very likely) to 4 (very unlikely).

Notes about Social Cohesion and Informal Social Control Items. The SNCS made two modifications to the measures of social cohesion and informal social control developed by Sampson and colleagues (1997). The first was the removal of one item from both scales. “People in this neighborhood do not share the same values,” was removed from the social cohesion scale, and “would you say that it is very likely, likely, unlikely, or very unlikely that neighbors could be counted on to intervene if the fire station closest to your home was threatened by budget cuts,” was removed from the informal social control scale (Matsueda, 2010). Although most studies use the informal social control items from the Sampson et al (1997) study, multiple studies have modified this measure. For example, Sampson, Morenoff, and Earls (1999) only used three items that focus on child-centered social control. Bruinsma and colleagues (2013) changed the informal social control item that asked how likely it was that neighbors would intervene if a fire station was threatened with budget cuts. Their measure focused on local community centers because of the way that Dutch fire stations are funded. Another study (Byrnes et al., 2011) removed the fire station item and the social cohesion item, “People in this neighborhood do not share the same values.”

The second modification to the measures of social cohesion and informal social control used by Sampson and colleagues (1997) was the removal of the ‘neutral’ response option, which resulted in four-point Likert scales (Matsueda, 2010). This modification is not common in previous research, and no rationale for this modification was given (Matsueda, 2015, personal communication, November 25, 2015). The data are ordinal in nature because of the number of response categories. The impact that the number of response categories has on analyses will be discussed later in this section, and the implications of the generalizability issues that result from modifications to the Sampson et al (1997) scales will be discussed in Chapter 5.

Upon examining the social cohesion and informal social control items, there is a possibility that the first item of social cohesion, "You can count on adults in this neighborhood to watch out that children are safe and don't get into trouble," may reflect informal social control because it pertains to the perception that neighbors will watch neighborhood children. To test for whether or not this is the case, three confirmatory factor analyses will be conducted. The first will be conducted where social cohesion and informal social control items are allowed to load on their respective concepts. The second will free the first social cohesion item so that it can load on both social cohesion and informal social control. The third set of analyses will remove the item from the analysis. This series of confirmatory factor analyses suggest that allowing the item to load on the social cohesion factor fit the data the best.

Mutual Efficacy. The SNCS contains five questions that reflect the efficacy of various community actors: small groups of neighbors; organized neighborhood associations or community clubs; police; local, state, or national officials; and doing things by oneself. Mutual efficacy will be measured by combining the following items: (1) how effective would the following approach be in resolving major problems around your neighborhood: small groups of neighbors working together, and (2) how effective would the following approach be in resolving major problems around your neighborhood: organized neighborhood associations or community clubs? These items were selected because they focus on collectives of community members. Response options on each item range from 1 (highly effective) to 3 (not at all effective).

Individual Level Variables

Demographics. The following demographic information will be utilized in this study: gender, age, marital/cohabitating status, number of children living at home, race, ethnicity, and foreign-born status. Gender is measured as a dichotomous Male/Female variable. Age is measured as a continuous variable. Marital status was originally coded with six response categories (Married, living with someone as a couple but not married, divorced, separated, widowed, and never married). However, the proportions of individuals that were divorced, separated, and widowed were small, so the response options will be recoded into married/cohabiting and not married/cohabiting. Race is measured using a series of dichotomous yes/no questions asking whether or not a respondent belonged to the following racial categories: White, Black, Asian, and Other[2]. Ethnicity is measured using a dichotomous yes/no question asking whether or not a respondent identifies as Hispanic or Latino. Foreign-born status is also measured using a dichotomous yes/no question indicating whether or not a respondent was foreign born.

Socioeconomic Status. Multiple measures will be used to reflect socioeconomic status. Years of education are measured using a continuous variable. Household income is measured using a categorical variable where respondents selected from three categories

[2] Although race is not included as a control variable in the structure model presented in this dissertation, it was included as a dichotomous variable (White/Non-White) in a supplementary path analysis that used regressions.

reflecting their annual household income: (1) under $25,000, (2) $25,000 to under $75,000 (3) over $75,000. Employment status is measured using a dichotomous yes/no variable indicating whether or not an individual was employed last year. Home ownership is measured with one item that is dichotomized to reflect home ownership or buying, and renting/other. Although "renting" and "other" were originally separate responses, they were combined because only 0.7% of respondents (n = 15) reported "other."

Neighborhood Clustering. Although the original SCNS data contained neighborhood level variables that were collected from the U.S. Census (Matsueda, 2010), the Census data are not available as part of the ICPSR data (Matsueda, 2015, personal communication, November 25, 2015). Because the Census Tract identifiers are randomly generated to protect respondents' identities, it is impossible to collect Census Data and merge them into the data set. The implications of the random tract identifiers will be discussed in Chapter 5.

Analyses

Screening for Missing Data. The data were screened for missing values using SPSS' v23 missing value analysis. This procedure determines both the amount, and nature of the missing data. As per the recommendation of SPSS (IBM/SPSS, 2015), it is safe to use listwise deletion when less than 5% of the cases are missing values and the data are missing at random; meaning that the missing values do not depend on other values in the data. In order to determine whether or not the data are missing at random, SPSS uses Roderick J. A. Little's chi-square statistic (Little, 1988), where a statistically significant (p<.05) chi-square indicates that data are not missing at random.

Multiple Imputation. The missing data analysis revealed that a listwise deletion would result in losing 28.6% (n=928) of cases. Further, the data are not missing at random (χ^2=2,644.11, *p*<.05); indicating that listwise deletion is not appropriate. Multiple imputation (MI) is the recommended method to replace missing data (McKnight, McKnight, Sidani, & Figuerdo, 2007). MI occurs in three phases: imputation, analysis, and pooling (Enders, 2010). The imputation phase draws information from variables in the dataset to estimate values for missing cases (Enders, 2010). The analysis phase then estimates the impact that the missing data have on estimates (McKnight et al., 2007). Standard errors are then adjusted in the pooling phase to give more accurate standard errors and confidence intervals (Enders, 2010).

According to Enders (2010), MI should be conducted at the item level in order to maximize the available data during imputation. MI was conducted using SPSS v23 (IBM/SPSS, 2015) with fully conditional specification (FCS). FCS was used because it imputes data by performing a series of regressions (van Buuren, Brand, Groothis, Oudshoorn, & Rubin, 2006). Because FCS is able to use linear, logistic, or multinomial regression to impute values, it is suited for datasets that include continuous, dichotomous, and categorical variables (van Buuren et al., 2006). Following previously established guidelines (Allison, 2001; Rubin, 1996), data will be imputed five times resulting in six data sets (the original data set and the five imputed data sets). Analyses will then pool estimates and standard errors, and then adjust the *p*-values and confidence intervals (McKnight et al., 2007; Rubin, 1987).

Another important decision to make when conducting MI is determining the variables that should be included in the process (Enders, 2010). At a minimum, MI should include all variables included in the analysis. However, auxiliary variables (e.g. variables that are not included in the analysis) can be included during MI to increase power and provide better estimates for missing values (Collins, Shafer, & Kam, 2001). Correlations were conducted among the variables included in the analysis and all other variables in the data set in order to identify auxiliary variables. As a result of this process, 167 additional variables were included in the MI phase.

Univariate Analyses. The following univariate analyses will be conducted to provide a description of the sample, ensure that the data meet the assumptions of statistical tests, and to enable a discussion about the generalizability of the findings: mean, standard deviation, and values of skewness and kurtosis. The histograms of variables will also be examined in order to assess for sparseness and univariate normality.

Internal Consistency. Although there are multiple methods of assessing the internal consistency of a measure, analyses in this paper will use a modified equation for Cronbach's alpha (α; Cornelius, Booker, Arthur, Reeves, & Morgan, 2004). Despite its widespread use in research, α is limited in terms of its use in MLCFA because it does not measure reliability at multiple levels of analysis (Cronbach, 1951; Geldhof, Zephyr, & Preacher, 2013). Further, Cronbach's alpha examines the correlations among items rather than the covariances among latent variables (Cronbach, 1951; Geldof et al., 2013). To account for this, α will be estimated using a process outlined in Geldhof and colleagues (2013, p. 73). In short, α is calculated by multiplying the squared number of items with the average covariance among items. This number is then divided by the variance of the scale. Measures with an α of 0.70 and above will have acceptable internal consistency

(Cronbach, 1951). Although multilevel α performs well in most situations, small cluster sizes can lead to overestimates in α at the between level (Goldhof et al., 2013).

Data Screening

Statistical assumptions that will be assessed include normality, linear relationships between independent variables, no influential outliers, and factorability (Bandalos & Finney, 2010). As suggested by Bandalos & Finney (2010), values of skewness and kurtosis that exceed 2.0 and 7.0 respectively will be considered non-normal. Histograms will also be examined in order to assess for normality and sparseness (Fabrigar et al., 1999). Linearity will be assessed by testing the curve fit between items measuring social cohesion, mutual efficacy, and informal social control. Univariate outliers can present a problem for statistical analyses as well, but outliers are not expected to be an issue because the response options of the social cohesion, mutual efficacy, and informal social control are quasi-interval in nature (Bandalos & Finney, 2010). However, outliers and invalid responses will be assessed by examining the frequency distributions of each survey item. Multivariate outliers will be assessed by conducting a regression using the variables in the analysis (Kline, 2005; Bollen, 1989).

Bivariate correlations between all variables will provide a preliminary check to see if multicollinearity may be a problem during analysis. Correlations will also indicate the expected of the relationships among variables. A correlation coefficient greater than 0.9 will indicate the presence of multicollinearity (Cohen, Cohen, West & Aiken, 2003). The variance inflation factor (VIF) for each predictor will also be examined with a VIF greater than 10 indicating high multicollinearity (Cohen et al., 2003). The independence of observations will be tested by examining residual plots between each predictor and the predicted scores on the outcome variable, and a scatterplot of the regression standardized residual and standardized predicted value will be examined to test for the homogeneity of variance (Cohen et al., 2003).

Exploratory Factor Analysis

RQ1: Are social cohesion, mutual efficacy, and informal social control unique factors on the individual level?

H1: Social cohesion, mutual efficacy, and informal social control are unique factors that are positively correlated with each other.

Statistical analysis: Exploratory factor analysis

A factor is a group of related variables that represent part of a construct (Tabachnick & Fidell, 2001). Factor analysis is a set of analytical techniques that allows researchers to understand the structure of constructs (Pett, Lackey, & Sullivan, 2003). There are two commonly used types of factor analysis: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA is typically used in exploratory research where the researcher does not know how many factors are needed to represent a construct (Leske, 1991). CFA is used when researchers have some knowledge about construct being studied and wish to test how well these factors fit the data (Nunnaly & Bernstein, 1994). Although demonstrating factorability of items with an EFA is not a sufficient justification to conduct a CFA on its own, it can be a useful starting point for a CFA provided that the analyses are adequately informed by theory (Bowen & Guo, 2011; Kline, 2005). This study will begin with an EFA in order to demonstrate that social cohesion, mutual efficacy, and informal social control are three separate but related concepts.

Factor extraction refers to the process that calculates the correlations among measured variables and their factors (Warner, 2013). Although there are many different methods of extraction that can be used in EFA, the two most common are principal components analysis (PCA), and principal axis factoring (PAF; Pett et al., 2003). PCA and PAF begin with a correlation matrix of all variables, and then attempt to re-create the matrix based on a smaller number of components or factors. A component is a group of variables that are clustered through PCA, and are grouped together based on the maximum amount of observed variance (common, specific, and error variance) explained by the component (Goddard & Kirby, 1976). For example, the variables that load on component 1 explain the largest proportion of observed variance, the variables that load on component 2 explain the second largest proportion of observed variance, and so on. A factor on the other hand, is based on the explained variance that is shared among variables (Nunnally & Bernstein, 1994). The variables that load on factor 1 share the most variance explained with one another, the variables that load on factor 2 share the second most variance explained and so on. While both PCA and PAF are used as data reduction techniques, PCA focuses more on determining the minimum number of components that are needed to explain a phenomenon whereas PAF examines how well certain variables ‘hang’ together on a factor (Pett et al., 2003).

This study will use PAF because it is the appropriate method of extraction when the goal of the study is to understand the number and nature of the underlying constructs (Costello & Osborne, 2005; Fabrigar, Wegener, MacCallum, & Strahan, 1999). PCA is not as useful in this dissertation because the number of constructs is expected to be 3 (social cohesion, mutual efficacy, and informal social control). PCA is also unable to differentiate between measurement error and shared variance, resulting in an overestimation of the relationships among variables (Pedhauzer & Schmelkin, 1991; Nunnally & Bernstein, 1994). PAF is also less sensitive to the scaling of variables, which is important given the differences in scaling for the measures of social cohesion, mutual efficacy, and informal social control (Pett et al., 2003).

Another key decision to make when conducting an EFA is deciding what method of rotation to use. Rotation is necessary because the goal of EFA is to achieve a simple structure, which requires that each factor contains variables with loadings that are close to zero (Harman, 1976). Factor extraction plots items in geometric space, using the correlations among items to plot the location of each item. It is difficult to determine if simple structure has been achieved because plotted points do not fall near any of the axes. Rotation keeps the items in place but turns the axes to increase the utility and interpretability of factors (Nunnally & Bernstein, 1994). Researchers have two broad classifications of rotations to choose from: orthogonal and oblique. Simply put, orthogonal rotations do not allow factors to covary whereas oblique rotations do. Although preventing factors from covarying may assist in reaching a simple solution, research suggests that this does not reflect reality because social cohesion and informal social control covary (Pett et al., 2003; Sampson et al., 1997). Further, it is necessary to test the covariation among factors in order to answer **RQ1**. Therefore, this study will use an oblique rotation.

Oblique rotations generate three matrices as part of their solution: a factor pattern matrix (referred to as pattern matrix hereafter), a factor structure matrix (referred to as structure matrix hereafter), and a factor correlation matrix. The factor loadings in the factor matrix reflect the effect of the factor on the item controlling for all other factors. The structure matrix represents the correlations of the individual item with the factors. The factor correlation matrix is a correlation matrix of the factors. Although selecting a matrix to interpret factor loadings will be discussed in the analysis plan section, each of these matrices are useful when interpreting the results of an oblique rotation (Nunnally & Bernstein, 1994).

Factorability will be assessed by examining a correlation matrix of all the social cohesion, mutual efficacy, and informal social control items, as well as the Kaiser-Meyer-Olkin score (KMO), the measure of sampling adequacy, and the Bartlett's test of sphericity. The items will be considered factorable if more than half of the inter-item correlations are an absolute value between 0.30 and 0.80 (Pett et al., 2003), KMO and measures of sampling adequacy values of at least 0.70 (Pett et al., 2003), extraction communalities between 0.30 and 0.70, and a significant Bartlett's test of sphericity (Costello & Osborne, 2005).

Factors will be retained if they have eigenvalues greater than 1.0, and scree plots will also be examined in order to see if the two methods report a consistent number of factors (DeVellis, 2012; Pett et al., 2003). Items will be retained on a factor if their factor loading is at least 0.30 and marker items are items with factor loadings of 0.80 and above (Bandalos & Finney, 2010). Both the pattern and structure matrix will be reported. However, decisions to retain items on factors will be made based on the structure matrix if factors are found to covary in the three-factor model (Pett et al., 2003). If the factors do not covary, decisions to retain factors will be based on the pattern matrix because the pattern and structure matrices should be similar with less covariance between factors (Pett et al., 2003). Items that crossload on factors will be evaluated based the conceptual framework of Sampson and colleagues (1997). These matrices will be used to answer **RQ1**: are social cohesion, mutual efficacy, and informal social control unique factors on the individual level? The strength of the correlations between factors will be evaluated based on the standards developed by Cohen (1988) where correlations above 0.10, 0.30, and 0.50 representing small, medium, and large effect sizes respectively.

Structural Equation Modeling

The analyses presented in this dissertation will use structural equation modeling (SEM) for two analyses: a multilevel confirmatory analysis (MLCFA) and a single-level structural model. Although these are two different types of SEM, there are commonalities among them in terms of how models are analyzed (Bowen & Guo, 2011; Kline, 2005). Analytical procedures that are similar between the two types of SEM will be discussed before going into specifics about each.

SEM refers to a family of statistical procedures that test the covariance matrices among indicators and latent variables (Kline, 2005). Indicators are measures of a quality that can be observed whereas a latent variable is a measure of an unobservable theoretical construct (Bowen & Guo, 2011; Kline, 2005). Latent variables are typically measured indirectly by multiple indicators (Bowen & Guo, 2011; Kline, 2005). SEM is able to test these relationships by beginning with the relationships among indicators that are known, and then estimating the unobservable relationships among indicators (Bowen & Guo, 2011). Put another way, the indicators put into an SEM have known correlations among them. Ordinary least squares regression will estimate the effect that these individual indicators have on a dependent variable that is also measured by one or more indicators. In SEM, researchers identify indicators that comprise latent variables. SEM then creates latent variables by estimating the covariances among these variables and then tests the relationships among latent variables (Bowen & Guo, 2011; Kline, 2005).

Univariate and multivariate statistics used to check the assumptions of statistical tests were described earlier in this chapter. However, it is important to discuss one assumption that is common to many SEM analyses that is violated in this study: SEM typically assumes that indicators are continuous and follow an approximately normal distribution (Bowen & Guo, 2011; Kline, 2005). Most studies treat the indicators of collective efficacy developed by Sampson and colleagues (1997) as continuous (Sampson et al., 2002; Sutherland et al., 2013). While this may not be an issue when the indicators are summed into one measure, it is problematic in SEM because the analysis examines the covariance among indicators (Kline, 2005). The SNCS uses a four-point Likert scale for social cohesion and informal social control indicators, and a three point Likert scale for mutual efficacy indicators. This means that these items are ordinal in nature (Kline, 2005). To account for this, this study will use a mean and variance adjusted weighted least squares estimator (WLSMV). In WLSMV, the bivariate correlations are estimated using polychoric correlations, which assumes that a normal distribution underlies the categorical indicators (Flora & Curran, 2004). Although researchers recognize that there is always a risk that this assumption is not met in the data, WLSMV remains the preferred method of conducting SEM with ordinal level data (Bowen & Guo, 2010; Byrne, 2012; Flora & Curran, 2004; Kline, 2005; Muthén & Muthén, 1998-2015).

Analysis Plan. Kline (2005, p. 91-92) states that there are six steps to SEMs: 1) specify the model, 2) evaluate model identification, 3) select the measures (collect, prepare and screen data), 4) estimate the model (assess model fit, interpret parameter estimates, and consider equivalent or near-equivalent models), 5) re-specify the model, and 6) report the results. Each step will be described in the following sections.

Specify the Model. Specification is considered to be the most important step of SEMs (Kline, 2005). In the specification step, researchers draw upon theory and prior research to develop a hypothesized model to be tested (Bollen, 1989; Bowen & Guo, 2011; Kline, 2005). A key part of model specification is determining the number of indicators that are needed to capture a latent variable (Kline, 2005). Some latent variables can have many indicators. It is up to the researcher to determine the theoretically relevant indicators. In SEMs, researchers must also determine the number of latent variables, and the indicators associated with those latent variables (Bollen, 1989; Bowen & Guo, 2011; Kline, 2005). Three latent variables are expected because social cohesion reflects a sense of belonging to a neighborhood; mutual efficacy is the belief that actions will be successful, and informal social control pertains to actions that residents take to informally monitor their neighborhood. Further, the results of the EFA will supplement the theoretical justification for specifying a three-factor model by determining whether or not social cohesion, mutual efficacy, and informal social control are unique constructs statistically.

Identification. The term identification means that, "It is theoretically possible for the computer to derive a unique estimate of every parameter" (Kline, 2005, p. 93). In short, the degrees of freedom of the SEM need to be greater than or equal to zero (Kaplan, 2009). The number of indicators should exceed the number of parameters to be estimated in the model (Bollen, 1989; Bowen & Guo, 2011; Kaplan, 2009; Kline, 2005). According to multiple statistics textbooks (Bowen & Guo, 2011; Byrne, 2012; Hoyle, 2012), Kline (2005) provides the most thorough discussion of model identification. Therefore, we will use the criteria stated in his book (Kline, 2005; p. 132-146). According to Kline (2005, p. 138), a structural model is identified if both the structure and measurement models are identified. Because the structural model in Appendix B is a recursive model, it is identified because all recursive structural models are identified (Kline, 2005, p. 132). Byrne (2012) provides a more in depth discussion of MLCFA than Kline (2005), and states that the two levels of a MLCFA are mirror images of one another. Therefore, identification needs to be determined on one level only. The measurement model in Appendix D is identified according to Kline's (2005, p. 138) rule of thumb that each latent variable should have two or more indicators. Model identification was also calculated using the following formula: k (k + 1)/ 2 where k is the number of indicators in a model (Kline, 2005). This number was subtracted by 23, which is the number of parameters that are to be estimated (3 variances for the latent variables, 3 covariances among latent variables, 7 factor loadings, and 10 measurement errors). Based on this method, the MLCFA is identified on both levels with 32 degrees of freedom. Because both the MLCFA and structural model are both identified, the model in Appendix B is identified.

Measure selection. As with any statistical analysis, it is important to use measures that are internally consistent, meet the assumptions of statistical tests, and reflect the concepts of interest (Bollen, 1989; Kline, 2005). Although the measures used in this dissertation were predetermined by the SNCS (Matsueda, 2010), the data will be screened using the procedures described above, and reliability estimates for factors derived from the MLCFA will be tested using the Cronbach's Alpha described earlier in this chapter (Chronbach, 1951).

Estimation. Three things take place during the model estimation step: 1) model fit is evaluated, 2) parameter estimates are interpreted, and 3) equivalent or near-equivalent models are considered (Kline, 2005). Model fit describes how well estimates derived from the model reflect the data. There are a number of reasons why models may fit the data poorly. For example, a model may be underidentified ($df < 0$) or just-identified ($df = 0$), the data may violate any of the statistical assumptions of SEM, or the sample size is too small (Bowen, 1989; Kline, 2005). Because some statistical programs will still run an SEM despite violations of some of these assumptions, it is critical that researchers screen their data carefully and check that their models are properly identified (Bowen & Guo, 2011; Kline, 2005).

Model Fit Indices. Fit indices examine how closely the covariance matrix of the specified model fit the sample covariance matrix observed in the data. With SEM, there is no one statistic that determines model fit. Rather, there are multiple fit statistics, each with their own strengths and limitations. The most commonly used fit indices for SEMS using WLSMV are: the model chi-square (χ^2_M), the root mean square error of approximation (RMSEA), the comparative fit index (CFI), the Tucker-Lewis Index

(TLI), the weighted root-mean square residual (WRMR), and the standardized root-mean square residual (SRMR). These fit indices will be described in the following paragraphs.

Model chi-square. The χ^2_M is the product of the value obtained by the WLSMV estimator and the sample size minus 1 (Kline, 2005). This statistic tells researchers whether or not the covariance matrices specified by the researcher are different from those in the data. Because researchers want their matrices to match those in the data, a non-significant χ^2_M suggests that the model fits the data well (Bollen, 1989; Bowen & Guo, 2011; Kline, 2005). One limitation of the χ^2_M is that it is difficult to obtain a non-significant value when sample sizes are large. This is due to the fact that sample size is used to calculate the χ^2_M. Because of this, it is common for researchers to conclude that the model can fit the data well even if the χ^2_M is statistically significant (Kline, 2005).

RMSEA. Much like the χ^2_M, the RMSEA tells researchers how closely the specified matrices match those in the data. However, the RMSEA is able to account for the complexity of the model (Bowen & Guo, 2011). As with ordinary least squares (OLS) regression, adding parameters will improve model fit because there is an additional predictor (Kline, 2005). The RMSEA is able to account for this by including the degrees of freedom into the calculation of model fit (Bowen & Guo, 2011). Using guidelines from Browne & Cudeck (1993), a RMSEA ≤ 0.05 indicates close approximate fit, values between 0.05 and 0.08 suggest reasonable fit, and values ≥ 0.10 indicate poor model fit.

CFI & TLI. The CFI measures the improvement of fit between the model developed by the researcher and a baseline model (Hu & Bentler, 1999; Kline, 2005). The TLI is the difference between χ^2/df for the null and researcher developed models divided by the difference between an ideal expected value (typically 1.0), and χ^2/df for the null model (Marsh, Balla, & McDonald, 1988) According to Hu & Bentler (1999), values above 0.95 indicate good fit for both the CFI and TLI.

WRMR. The weighted root-mean square residual (WRMR) was developed by Muthén & Muthén (1998-2015). This index measures the weighted average differences between the sample and estimated population variances and covariances (Yu, 2002). Because WRMR is understudied compared to fit indices developed for continuous measures, the cutoff values for WRMR can vary depending on factors like sample size, the level of measurement of indicators, and the number of latent variables in the model (Hsu, 2009; Yu, 2002). However, many researchers state that a WRMR less than or equal to 0.90 is a good cutoff for most cases (Hsu, 2009; Muthén & Muthén, 1998-2015; Yu, 2002).

SRMR. The standardized root-mean squared residual (SRMR) is a fit index that reflects the standardized difference between the observed correlation and the predicted correlation (Hu & Bentler, 1999). Two versions of this index are produced at both the within and between group level. Hu and Bentler (1999) suggest that SRMR values less than 0.08 generally reflect acceptable model fit. The SRMR will only be reported for the multilevel confirmatory factor analysis because it is a fit index for multilevel models (; Muthén & Muthén, 1998-2015).

Respecification. If the fit of the initial model is poor, researchers are required to respecify their models until either adequate model fit is obtained, or it appears that a theoretically consistent solution cannot be obtained (Bollen, 1989; Bowen & Guo, 2011; Kline, 2005). The process of respecification is identical to specification other than the fact that respecification only occurs if the original model fit is poor (Bowen & Guo, 2011). However, multiple researchers state that it is imperative that any changes to the model are informed by theory and are not made simply to improve to model fit (Bollen, 1989; Bowen & Guo, 2011; Kline, 2005).

Multilevel Confirmatory Factor Analysis

RQ2: Do measures of social cohesion, mutual efficacy, and informal social control fit the data better as a one, two, or three factor model at both the individual level and neighborhood level?

H2: The three factor model will fit the data better at the individual level and neighborhood level.

Statistical analysis: Multilevel confirmatory factor analysis

Although EFA and CFA are similar in terms of determining which indicators can be combined into scales, they are very different in their method (Bowen & Guo, 2011). Whereas EFA is typically viewed as a data driven approach to determining the number of factors that a particular set of items measure, CFA is theory driven (Bowen, 1989). EFA examines the variance explained by items in order to identify the minimum number of factors required to measure a construct (Bowen & Guo, 2011). Researchers then combine these items into scales that measure concepts (e.g. collective efficacy). In CFA, the researcher determines both the number of latent variables, and the indicators that are expected to load on each latent variable. CFA then determines how well the indicators load on the latent variables, and how well the model developed by the researcher fit the data (Kline, 2005).

Bollen (1989) identifies three key limitations to EFA that CFA is able to address. First, EFA does not allow researchers to constrain factors to zero. For example, in studies with repeated measures it is impossible for researchers to specify that measures collected at a later time point should not have an influence on measures at earlier time points. Second, EFA does not allow measurement errors to correlate. This is problematic because there may be measurement error on the indicator level because of data collection method (e.g. phone v. mail survey), or bias in the ordering of questions. Not accounting for measurement error can cause EFA to draw misleading conclusions about factors. The third limitation of EFA pertains to the fact that EFA can only specify that all factors are correlated or none of the factors are correlated. This is an issue because factors may not be correlated to one another directly, but are related due to a third factor; which can be the case in mediation models like the one tested in this dissertation.

Multilevel Confirmatory Factor Analysis. One of the assumptions of many statistical tests is that errors in the data are independent of one another (Bowen & Guo, 2011; Cohen, et al., 2003; DeVellis, 2012; Kline, 2005). Neighborhood data often violate this assumption however, because respondents are nested within neighborhood (Raudenbush & Sampson, 1999). Because many statistical tests do not take this clustering into account, estimates of error variance are too small; potentially biasing findings (Cohen et al., 2003; Raudenbush & Bryk, 2002). Multilevel modeling (MLM) is able to account for the clustering in data by estimating the variation that occurs both within groups and between groups, and applies a formula to correct the standard errors (Hox, 2010).

Although non-independence can be considered a statistical issue, it is also the foundation of neighborhood research. Researchers study neighborhoods because individuals within the neighborhood share experiences associated with belonging to that neighborhood. These experiences can in turn shape the neighborhood and the residents who reside in them (Bursik & Grasmick, 1993; Shaw & McKay, 1942, 1969; Wilson, 1987). In addition to the statistical issues mentioned above, concepts like social cohesion, mutual efficacy, and informal social control that are measured on the individual level are community level concepts and therefore, should be modeled on the community level (Sampson & Raudenbush, 1999).

MLCFA combines multilevel modeling and structural equation modeling (Rabe-Hesketh, Skrondal, & Zheng, 2007). MLM is an extension of multiple regression because it includes a grouping variable. MLCFA is an extension of MLM that models within and between group variation of latent variables (Byrne, 2012; Rabe-Hesketh et al., 2007). An illustration of the MLCFA to be tested can be found in Appendix D. One of the challenges with MLCFA is statistical power because power is now calculated based on the grouping variable (neighborhood). Hox and Maas (2001) suggest that the grouping variable should have a sample size of approximately 100. Because the SNCS data are comprised of 123 neighborhoods, the SNCS data are suitable for MLCFA.

Analysis Plan. The MLCFA will be built using the four-step procedure developed by Muthén (1994) that is outlined in Byrne (2012). After screening the data, the first step is to conduct a CFA on the total sample (i.e. not accounting for clustering by neighborhood). This step is necessary as it provides support for the hypothesized factor structure developed by the researcher. If the factor structure does not adequately fit the data or if the model can be improved, the researcher can make changes to the model as they would any other confirmatory factor analysis. Once the measurement model has been developed on the individual level, the researcher tests two CFAs simultaneously: one occurring on the individual level and the other occurring on the group level. Although originally viewed as two separate steps (Muthén, 1994), advances in statistical software allows researchers to conduct both analyses simultaneously. The fourth step in MLCFA is examining the intraclass coefficients (ICC) of each indicator. The ICC is the, "Proportion of variance in the outcome that is between groups (Raudenbush & Bryk, 2002, p. 36)," and describes the extent to which nesting may bias the findings. Groves (1989) states that even relatively small ICCs can have a significant impact on the findings produced from clustered samples. Early guidelines from Muthén (1997) suggest that researchers should definitely use MLCFA with ICCs greater than 0.10. Later guidelines state that MLCFA is acceptable even if ICCs are below 0.10 (Julian, 2001; Selig, Card, & Little, 2008). This study will use the criteria of Kreft & de Leeuw (1998) who state that ICCs as small as 0.05 can increase the likelihood of making type I error.

One of the challenges of determining model fit in MLCFA is that the fit indices that are computed are based on the entire model. This means that the fit indices for the between and within group models are combined. Because the sample sizes are larger for the within group model (individual) than the between group model (neighborhood), fit indices are generally dictated by the within group model (Hox, 2002). Although approaches have been developed to analyze fit indices on both levels individually (Ryu & West, 2009; Yuan & Bentler, 2007), these approaches are problematic and will not be used in this study (Byrne, 2012). Therefore, fit indices for the overall model will be interpreted using the criteria that were described earlier.

Structural model

RQ3: What are the relationships among social cohesion, mutual efficacy, and informal social control?

H3a: A model where mutual efficacy mediates the relationship between social cohesion and informal social control (Mutual Efficacy Model; Appendix B) will fit the data better than the current collective efficacy model that combines social cohesion and informal social control (Appendix C).

Statistical analysis: Structural equation modeling

H3b: The relationship between social cohesion and informal social control will be at least partially mediated by mutual efficacy (Appendix B).

Statistical analysis: Structural equation modeling

RQ4: Does the mutual efficacy model predict neighborhood disorder?

H4: There will be a negative association between mutual efficacy and neighborhood disorder where higher levels of mutual efficacy is associated with lower levels of neighborhood disorder through mutual efficacy's relationship with informal social control.

Statistical analysis: Structural equation modeling

Structural models build upon the analyses conducted in CFAs. Whereas CFA is used to determine the number of latent variables present in a set of measures, a structural model establishes directional relationships among the latent variables (Bollen, 1989;

Bowen & Guo, 2011; Byrne, 2012; Kline, 2005). Because data in this study are cross sectional in nature, causality cannot be established (Bowen & Guo, 2011; Kline, 2005). However, the theoretical justification for the paths estimated in this model are described in Chapter 3. Another difference between CFAs and structural models is that latent variables can be broken down into two types: exogenous and endogenous. Endogenous variables are determined by variables included in the model whereas the causes of exogenous variables are outside of the specified model. Appendix B is the structural model of the refined model of collective efficacy to be tested in this study. As seen here, social cohesion, mutual efficacy, and informal social control are endogenous variables and neighborhood characteristics (income, resident mobility, and employment) are exogenous variables.

Analysis Plan

The structural model adds three steps to the MLCFA (Bowen & Guo, 2011). The first step is adding observed structural variables into the structural model. For the purpose of this study, income, resident mobility, and employment are the structural variables, which are expected to have an impact on all other latent variables. Next, researchers need to specify the relationships among variables. The model in Appendix B frames mutual efficacy as a variable that mediates the relationship between social cohesion and informal social control. The third step is to add structural error terms to the endogenous variables in order to reflect the variation in the variables that are not explained by predictors (Bowen & Guo, 2011). The researcher will then assess the fit of the structural model. Because the fit indices and cutoffs are the same for CFA and structural models (χ^2_M, RMSEA, CFI, TLI, and WRMR), they will not be described here.

The support for structural models is improved when they are tested against alternative models. There are two different types of models that can be tested: nested and non-nested (Kline, 2005). A nested model occurs where the alternative model is a subset of the researcher developed model whereas non-nested models are not a subset of the researcher developed model. This study will compare the model in Appendix B with the current model of collective efficacy (Appendix C). Typically, researchers can compare nested models by conducting a chi-square to determine if one model is a significantly better fit of the data (Kline, 2005). However, this procedure does not work with WLSMV because of the method used to calculate the χ^2_M (Muthén & Muthén, 1998-2015). Therefore, both models will be compared using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Typically speaking, smaller values of AIC and BIC indicate better model fit (Bowen & Guo, 2011).

Software

This study conducted all data management, missing value analyses, data screening and descriptive analyses using IBM SPSS statistics version 22 (IBM/SPSS, 2015). The EFA, MLCFA and structural model were analyzed using Mplus version 7.4 (Muthén & Muthén, 1998-2015).

Conclusion – Chapter 4

The next chapter will present the results that answer the research questions using the analysis plan described above. This includes screening the data; creating the imputed datasets, reporting univariate statistics and the internal consistency of measures; and conducting the EFA, MLCFA, and structural model. Analyses will be conducted on the original dataset that using listwise deletion to remove cases with missing data, as well as the imputed datasets. The results of this sensitivity analysis will then be compared to determine if the MI had an impact on the findings. The findings of the study will then be presented and the implications and conclusions of the study will be discussed.

Chapter 5 – Results

This chapter will describe the Seattle Neighborhoods and Crime Survey (SNCS) sample and provide a brief discussion of how the SNCS sample compares to the Census estimates for the population of Seattle in 2000. The univariate results pertaining to the focal predictors will then be described. The following sections will then present results that answer each research question. The limitations of this dissertation will then be discussed. Chapter 5 will conclude with a summary of the findings.

Univariate Statistics

Descriptive Statistics. Table 1 contains the descriptive characteristics of the SNCS sample (n = 3,365). The median age of the sample is 47.0 years old, and slightly more than half (51.90%, n = 1,747) is female. The overwhelming majority (72.80%, n = 2,423) of respondents are white with the next two largest ethnic groups being Asian (7.90%, n = 263) and Multiracial (7.18%, n = 239). In terms of racial diversity, the Blau Index suggests that there is roughly a 50% chance that two randomly selected individuals in the sample will be of a different race. The majority (>50%) of the sample also reports that they were born in the United States, and are married or cohabiting. Two-thirds of the sample report graduating from either a college or trade school (38.39%, n = 1,287), or obtaining a degree from a graduate or professional school (28.78%, n = 965), and were employed at the time of the interview (66.95%, n = 2,253). Over half (51.79%, n = 1,742.8) of the sample earns between $25,000 and $75,000 annually compared to 17.36% (n = 584.2) earning less than $25,000 and nearly one-third (30.84, n = 1,038) earning greater than $75,000 annually. In terms of family disruption, only 5.0% (n = 168) of respondents are the heads of single parent households. The majority of respondents have not been living at their current address for five years (85.25%, n = 2,872), and two-thirds (67.39%, n = 2,872) of the sample is renters. The number of respondents per neighborhood ranged from 11 to 29 with an average of 18.05 (3.51).

Table 1 – SNCS Sample Descriptives

Variable	N = 3,365
Female	1,747 (51.91%)
Age (median)	47.0
Married/Cohabiting[a]	1,801 (53.97%)
Race/Ethnicity[b]	
White	2,423 (72.80%)
Black	185 (5.55%)
Asian	263 (7.90%)
Pacific Islander	17 (0.51%)
Hispanic or Latino	97 (2.91%)
Native American	20 (0.60%)
Other	84 (2.52%)
Multiracial	239 (7.18%)
Blau Index	0.54 (0.19)
Foreign Born	492 (14.62%)
Education[c]	
Less Than HS/GED	134 (4.00%)
HS/GED	346 (10.32%)
Some College	629 (18.76%)
College or Trade School Graduate	1,287 (38.39%)
Graduate/ Professional School Graduate	965 (28.78%)
Currently Employed	2,253 (66.95%)
Income	
Under $25,000	584.2 (17.36%)
$25,000 to Under $75,000	1,742.8 (51.79%)
Over $75,000	1,038 (30.84%)
Single Parent Household	168 (4.99%)
Resident Mobility	1,524 (45.3%)
Own Home/Buying	2,267 (67.39%)

[a] n = 3,337 because 3 individuals responded “don’t know” and 25 refused to respond
[b] n = 3,328 because 11 individuals responded “don’t know” and 26 refused to respond
[c] n = 3,352 because 3 individuals responded “don’t know” and 10 refused to respond

SNCS Sample and Seattle Comparison. The descriptive information for the SNCS sample as well as the 2000 Census estimates for the city of Seattle, WA (Census, 2016) can be found in Table 2. The median age for the SNCS sample was roughly 12 years older, and a larger proportion of the SNCS sample identified as white compared to the city of Seattle. A larger proportion of individuals in the SNCS sample owned their home, graduated from a graduate or professional school, and made over $75,000 in the previous year. The SNCS sample is older, more white, and of a higher socioeconomic status compared to the city of Seattle as a whole. The implications of these differences will be discussed at the end of the chapter.

Table 2 – Comparison of SNCS sample and 2000 Census Estimates for Seattle, WA

Variable	SNCS (n = 3,365)	2000 Census (n = 563,374)
Female	1,747 (51.9%)	282,130 (50.07%)
Own Home/Buying	2267.8 (67.39%)	304,222 (54.00)%
Age (median)	47.0	35.4
Education		
HS/GED or Below	480 (14.32%)[a]	105,649 (25.79%)
Some College	629 (18.76%)[a]	84,218 (20.56%)
College or Trade School Graduate	1,287 (38.39%)[a]	148,822 (36.34%)
Graduate/ Professional School Graduate	965 (28.78%)[a]	70,893 (17.30%)
Married/Cohabiting	1,801 (53.97%)[b]	202,865 (41.43%)
Employed	2,253 (67.0%)	321,524 (66.27%)
Income		
Under $25,000	584.2 (17.36%)	66,580 (25.74%)
$25,000 to Under $75,000	1742.8 (51.79%)	151,012 (58.38%)
Over $75,000	1,038 (30.84%)	41,043 (15.87%)
Race/Ethnicity		
White	2,619.4 (78.7%)[c]	394,925 (70.1%)
Black	242.4 (7.2%)[c]	47,323 (8.4%)
Asian	318 (9.56%)[c]	73,802 (13.1%)
Pacific Islander	47.2 (1.41%)[c]	2,817 (0.5%)
Native American	100.2 (3.01%)[c]	5,634 (1.0%)
Other	133 (3.99%)[c]	38,873 (6.9%)
Hispanic or Latino	173 (5.19%)[c]	30,986 (5.5%)

[a] n = 3,352 because 3 individuals responded “don’t know” and 10 refused to respond
[b] n = 3,337 because 3 individuals responded “don’t know” and 25 refused to respond
[c] n = 3,328 because 11 individuals responded “don’t know” and 26 refused to respond. Numbers differ from Table 1 because “multiracial” was not used, and values do not add up to 100% because an individual can belong to multiple groups.

Neighborhood Disorder. Table 3 contains the descriptive information for the neighborhood disorder and focal predictor items. As seen in Table 3, litter, garbage, or trash on the streets is considered to be the most serious problem out of all of the neighborhood disorder indicators with the majority (52.57%, n = 1,769) of respondents perceiving litter, garbage, or trash to be either a small (38.63%, n = 1,300) or big

(13.94%, n = 469) problem in their neighborhood (*Mdn* = 2.00, range = 1-3). Nearly three-quarters (72.14%, n = 2,427.6) of the sample did not consider abandoned houses and run-down buildings to be a problem in their neighborhood (*Mdn* = 1.00, range = 1-3).

Focal Predictors. Overall levels of mutual efficacy appear to be high in the sample even though the median and range were identical for both items (*Mdn* = 2.00; range = 1-3). The majority of respondents felt that small groups of neighbors would either be highly effective (47.46%, n = 1,597) or somewhat effective (45.11%, n = 1,518) at addressing neighborhood issues. Although fewer respondents indicated that organized neighborhood associations or clubs would be highly effective (30.62%, n = 1,030.2) at addressing neighborhood issues; over half (56.81%, n = 1,911.8) indicated that these groups would be somewhat effective. Very few respondents indicated that small groups of neighbors or organized groups would not be effective at addressing neighborhood issues (7.43%, n = 250 and 12.57%, n = 423.0 respectively).

Social cohesion also appears to be high in the SNCS sample. The "People are willing to help their neighbors" item was the most frequently selected with 91.93% (n = 3,093.8) of the sample stated that they agree (66.8%, n = 2,244) or strongly agree (25.25%, n = 849.8) with the item (*Mdn* = 2.00 range = 1-3). Despite being the least endorsed social cohesion item, 66.55% (n = 2,239.6) of respondents stated that they either strongly agree (18.89%, n = 635.8) or agree (47.66%, n - 1,604.8) that adults in the neighborhood know who the local children are (*Mdn* = 2.00, range = 1-3).

Table 3 – Frequencies of Neighborhood Disorder and Focal Predictors

Neighborhood Disorder				
	Not a Problem		A Small Problem	A Big Problem
Groups of teenagers hanging around on the streets	2,142.8 (63.68%)		883.6 (26.25%)	338.6 (10.06%)
Litter, garbage, or trash on the streets	1,596 (47.43%)		1,300 (38.63%)	469 (13.94%)
Spray painted graffiti on buildings and streets	2,168.0 (64.43%)		968.8 (28.79%)	228.2 (6.78%)
Abandoned houses and run-down buildings	2,427.6 (72.14%)		746.6 (22.19%)	190.8 (5.67%)
Neighbors causing trouble or noise	1,908.2 (56.71%)		1,143.4 (33.98%)	313.4 (9.31%)
Mutual Efficacy				
	Highly Effective		Somewhat Effective	Not at All Effective
Efficacy of small groups of neighbors	1,597 (47.46%)		1,518 (45.11%)	250 (7.43%)
Efficacy of organized neighborhood associations or clubs	1,030.2 (30.62%)		1,911.8 (56.81%)	423.0 (12.57%)
Social Cohesion				
	Strongly Agree	Agree	Disagree	Strongly Disagree
Count on adults to watch out that children are safe	808.6 (24.03%)	1,819.4 (54.06%)	646.8 (19.22%)	90.2 (2.68%)
People in this neighborhood can be trusted	855.6 (25.42%)	2,125.4 (63.16%)	323.6 (9.61%)	60.4 (1.79%)
Adults in the neighborhood know who the local children are	635.8 (18.89%)	1,603.8 (47.66%)	971.6 (28.87%)	153.8 (4.57%)
People are willing to help their neighbors	849.8 (25.25%)	2,244 (66.68%)	248.4 (7.38%)	22.8 (0.68%)
Informal Social Control				
	Very Likely	Likely	Unlikely	Very Unlikely
If children were skipping school	617.4 (18.35%)	1,072.0 (31.86%)	1,298.0 (38.57%)	377.6 (11.22%)
If children were spray painting graffiti	1,679.0 (49.90%)	1,277.0 (37.95%)	326.4 (9.70%)	82.6 (2.45%)
If a child was disrespecting an adult	391.0 (11.62%)	1,253.8 (37.26%)	1,357.8 (40.35%)	362.4 (10.77%)
If children were fighting on the street	1,148 (34.12%)	1,491 (44.31%)	587 (17.44%)	139 (4.13%)

Responses on the informal social control items varied widely compared to the mutual efficacy and social cohesion items. The majority of respondents stated that it was likely or very likely that neighbors would intervene if children were spray painting graffiti (87.85%, n = 2,956; *Mdn* = 1.0, range = 1-3)) or fighting in the street (78.43%, n = 2,639; *Mdn* = 1, range = 1-4). However, roughly half of the sample said it was likely or very likely that residents would intervene if children were skipping school (50.21%, n = 1,675.6; *Mdn* = 2, range = 1-4) or if a child was disrespecting an adult (48.88%, n = 1,7202; *Mdn* = 3.00, range = 1-4).

Few respondents endorsed the most negative response options on items pertaining to neighborhood disorder, social cohesion, and informal social control. Post-hoc sensitivity analyses were conducted for each of the following analyses where the negative response options were combined. Findings were consistent between the analyses that measured social cohesion and informal social control with three and four response options. Therefore, items were kept in their original scaling for analyses.

Exploratory Factor Analysis

RQ1: Are social cohesion, mutual efficacy, and informal social control unique factors on the individual level?

H1: Social cohesion, mutual efficacy, and informal social control are unique factors that are positively correlated with each other.

Statistical analysis: Exploratory factor analysis

Findings from the exploratory factor analyses (EFA) are presented in Table 4. EFAs were conducted to test four models: a one-factor, two-factor, three-factor, and unconstrained model. Both scree plots and eigenvalues suggest that the data are best represented by a three-factor solution. The structure matrix suggests that the items had the strongest factor loading on their expected factors (mutual efficacy, social cohesion, and informal social control). However, social cohesion and informal social control items also have strong cross-loadings. This is most likely due to the fact that there is a strong correlation between these factors (r = 0.67), which is consistent with previous research. Mutual efficacy is also correlated with social cohesion (r = 0.37) and informal social control (r = 0.31), though these correlations are weak. Taken as a whole, findings from the EFA suggest that mutual efficacy, social cohesion, and informal social control are three separate, though positively correlated constructs.

Table 4 – Exploratory Factor Analysis Factor Loadings

Variable	Mutual Efficacy	Social Cohesion	Informal Social Control
How effective would of small groups of neighbors be at resolving major problems around your neighborhood?	**<u>0.893</u>**	0.333	0.289
How effective would of small groups of neighbors be at resolving major problems around your neighborhood?	**<u>0.627</u>**	0.252	0.216
You can count on adults in this neighborhood to watch out that children are safe and don't get into trouble.	0.268	**<u>0.821</u>**	0.600
People in this neighborhood can be trusted	0.316	**<u>0.824</u>**	0.492
Adults in this neighborhood know who the local children are	0.241	**<u>0.703</u>**	0.551
People around here are willing to help their neighbors	0.354	**<u>0.793</u>**	0.552
How likely is it that neighbors would intervene if a group of neighborhood children were skipping school and hanging out on a street corner?	0.258	0.530	**<u>0.772</u>**
How likely is it that neighbors would intervene if some children were spray-painting graffiti on a local building?	0.280	0.524	**<u>0.735</u>**
How likely is it that neighbors would intervene if a child was disrespecting an adult?	0.174	0.422	**<u>0.670</u>**
How likely is it that neighbors would intervene if children were fighting out in the street?	0.263	0.515	**<u>0.762</u>**
Factor Correlation Matrix			
Mutual Efficacy	--		
Social Cohesion	0.37	--	
Informal Social Control	0.31	0.67	--

Note. Bold and underlined factor loadings indicate the factor on which the item was retained.

Multilevel Confirmatory Factor Analysis

RQ2: Do measures of social cohesion, mutual efficacy, and informal social control fit the data better as a one, two, or three factor model at both the individual level and neighborhood level?

H2: The three factor model will fit the data better at the individual level and neighborhood level.

Statistical analysis: Multilevel confirmatory factor analysis (MLCFA)

Table 5 – MLCFA Fit Indices

Fit Index	One Factor	Two Factor	Three Factor	Fit Criteria
χ^2_M	2,205.63*	1,412.87*	269.99*	non-significant
RMSEA	0.12	0.09	0.38	≤ 0.05 close fit 0.05-0.08 reasonable fit ≥ 0.10 poor fit
CFI	0.67	0.79	0.96	> 0.95
TLI	0.57	0.72	0.96	> 0.95
SRMR Within	0.09	0.07	0.03	< 0.08
SRMR Between	0.05	0.04	0.04	< 0.08

**p* < 0.05

Table 5 contains the fit indices for the one, two, and three factor MLCFA. Findings from the MLCFA mirror those from the EFA – namely, that the three-factor solution fits the data better than the one or two factor models. The three-factor MLCFA meets criteria for acceptable fit based on the root mean square error of approximation (RMSEA; 0.38), comparative fit index (CFI; 0.96), Tucker-Lewis index (TLI; 0.96), and the standardized root-men square residual (SRMR) for within (0.03) and between groups (0.04). The χ^2_M is statistically significant, which indicates poor fit based on this test. This means that the covariance matrices specified in the model are significantly different from those in the data. However, this statistical test is very sensitive to large sample sizes and should be interpreted cautiously (Kline, 2005).

Both the one-factor and two-factor models had statistically significant model χ^2_M and failed to meet criteria on the CFI (one-factor = 0.67; two-factor = 0.79) and TLI (one-factor = 0.57; two-factor = 0.72). The one-factor model failed to meet fit criteria on the RMSEA (0.12) and the SRMR within (0.09) though the model did meet criteria on the SRMR between (0.05). The two-factor model met criteria for poor fit on the RMSEA (0.09), and both the SRMR within (0.07) and SRMR between (0.04). Based on all of the fit indices, it can be concluded that the three-factor model had acceptable fit overall, and that the three-factor solution fits the data better than the one or two-factor solutions. Because of this, the remainder of this section will focus on the findings from the three-factor MLCFA.

The intraclass correlation coefficients (ICC; Table 6) reflect how correlated items are on the neighborhood level. The ICCs for individual items ranged from .049 to .154, indicating that roughly 5 to 15 percent of the variance in these items can be attributed to neighborhood. Figure 2 displays the results of the MLCFA. All items have factor loadings of 0.70 or higher for their respective latent factor on the within neighborhood level. Between neighborhoods, factor loadings varied from 0.58 to 0.99. In terms of correlations among the latent variables, mutual efficacy is significantly ($p < 0.001$) correlated with both social cohesion and informal social control both within ($r = 0.70$ for social cohesion and $r = 0.44$ for informal social control) and between neighborhoods ($r = 0.24$ for social cohesion and $r = 0.18$ for informal social control). Although social cohesion and informal social control are statistically indistinguishable from one another within neighborhoods ($r = 1.03$, $p < 0.001$), they are considered to be two correlated, though distinct concepts when examined between neighborhoods ($r = 0.33$, $p = 0.001$).

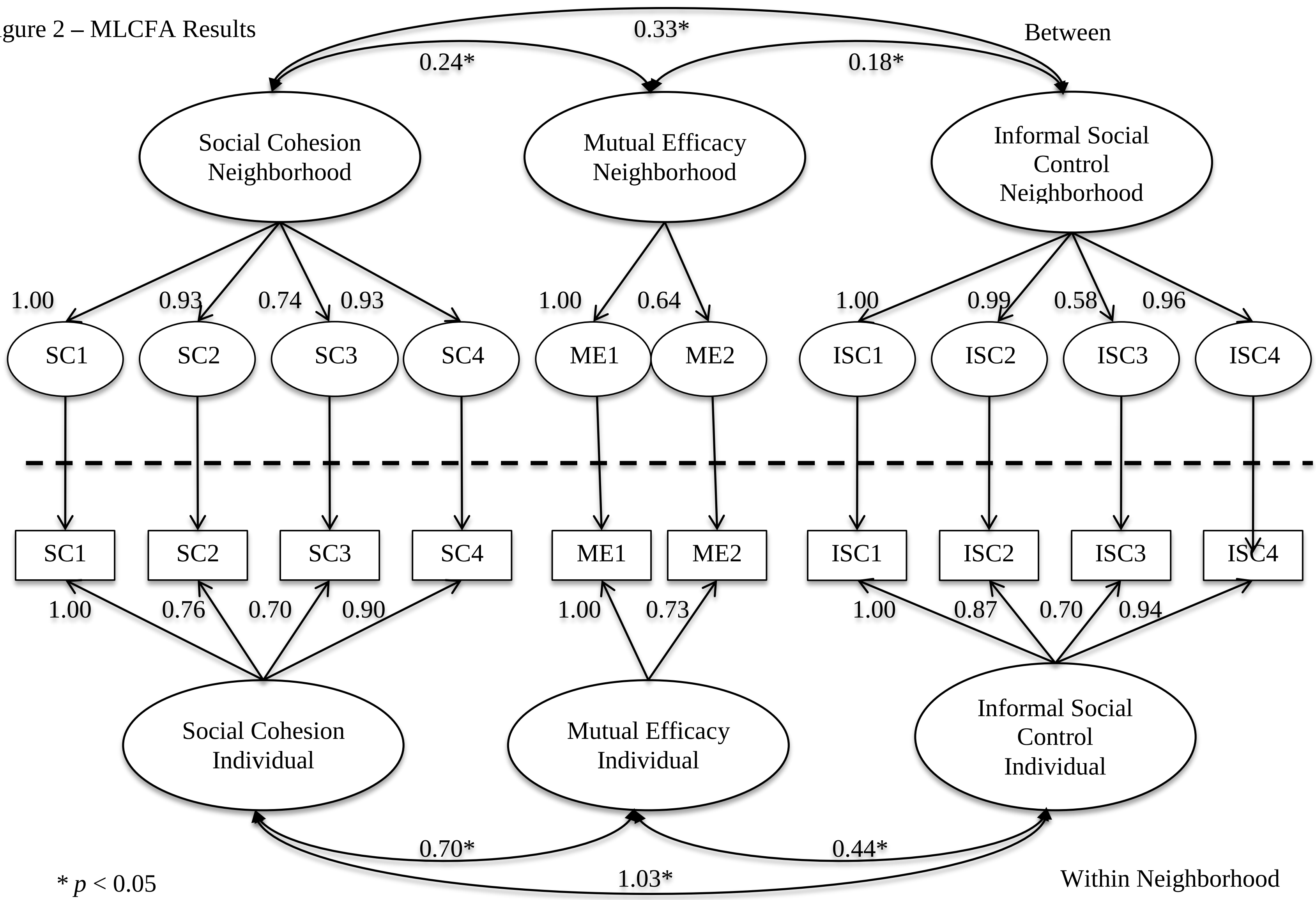
Despite the high correlation between social cohesion and informal social control within neighborhoods, findings from the MLCFAs suggest that social cohesion, mutual efficacy, and informal social control are better represented as three unique neighborhood level concepts. Further, none of the modification indices produced by Mplus suggested separating social cohesion and informal social control. When taken together, these findings suggest that social cohesion and informal social control are better modeled as two separate constructs.

Table 6 – Intraclass Correlation Coefficients

Variable	ICC
How effective would of small groups of neighbors be at resolving major problems around your neighborhood?	0.050
How effective would of small groups of neighbors be at resolving major problems around your neighborhood?	0.050
You can count on adults in this neighborhood to watch out that children are safe and don't get into trouble.	0.125
People in this neighborhood can be trusted	0.154
Adults in this neighborhood know who the local children are	0.103
People around here are willing to help their neighbors	0.133
How likely is it that neighbors would intervene if a group of neighborhood children were skipping school and hanging out on a street corner?	0.103
How likely is it that neighbors would intervene if some children were spray-painting graffiti on a local building?	0.106
How likely is it that neighbors would intervene if a child was disrespecting an adult?	0.049
How likely is it that neighbors would intervene if children were fighting out in the street?	0.092

Both social cohesion and informal social control are internally consistent at both the individual and neighborhood level. Cronbach's alpha for social cohesion is 0.765 at the individual level and 0.990 at the neighborhood level. For informal social control, Cronbach's alpha is 0.721 at the individual level and 0.985 at the neighborhood level.

Figure 2 – MLCFA Results



* $p < 0.05$

Structure Model

RQ3: What are the relationships among social cohesion, mutual efficacy, and informal social control at the neighborhood level?

H3a: A model where mutual efficacy mediates the relationship between social cohesion and informal social control (Mutual Efficacy Model; Appendix B) will fit the data better than the current collective efficacy model that combines social cohesion and informal social control (Appendix C).

Statistical analysis: Structural equation modeling

H3b: The relationship between social cohesion and informal social control will be at least partially mediated by mutual efficacy (Appendix B).

Statistical analysis: Structural equation modeling

Table 7 – Structure Model Fit Indices

Fit Index	Mutual Efficacy Model	Current Collective Efficacy Model	Fit Criteria
χ^2_M	916.99*	2,454.89*	non-significant
RMSEA	0.04	0.07	≤ 0.05 close fit 0.05-0.08 reasonable fit ≥ 0.10 poor fit
CFI	0.98	0.93	> 0.95
TLI	0.97	0.92	> 0.95
WRMR	1.88	3.29	≤ 0.90
AIC	787.99	2,192.89	smaller values indicate better fit
BIC	957.59	2,487.37	smaller values indicate better fit

* $p < 0.05$

As seen in Table 7, the χ^2_M for mutual efficacy and current collective efficacy models are statistically significant, and neither model met criteria on the weighted root-mean residual (WRMR; mutual efficacy model = 1.88, collective efficacy model = 3.29). However, the WRMR should be interpreted cautiously because it can be inflated in nested data, which is the case for the SNCS sample (Hsu, 2009). The mutual efficacy model demonstrates close fit on the RMSEA (0.04), and meets fit criteria on the CFI (0.98), and TLI (0.97). The collective efficacy model demonstrates reasonable fit on the RMSEA (0.07), but did not meet criteria on any of the other fit indices (CFI = 0.93, TLI = 0.92). Further, the AIC and BIC are both smaller for the mutual efficacy model. While it cannot be determined if the differences between these models are statistically significant, **H3a** is supported because the majority of the fit indices suggest that the mutual efficacy model fits the data better than the current model of collective efficacy.

Figure 3 depicts the results of the structure model[3]. As seen in the model, the paths from social cohesion to mutual efficacy, and from mutual efficacy to informal social control are all statistically significant. Further, social cohesion has a significant direct effect on informal social control. **H3b** is supported because, mutual efficacy partially mediates the relationship between social cohesion and informal social control.

RQ4: Does the mutual efficacy model predict neighborhood disorder?

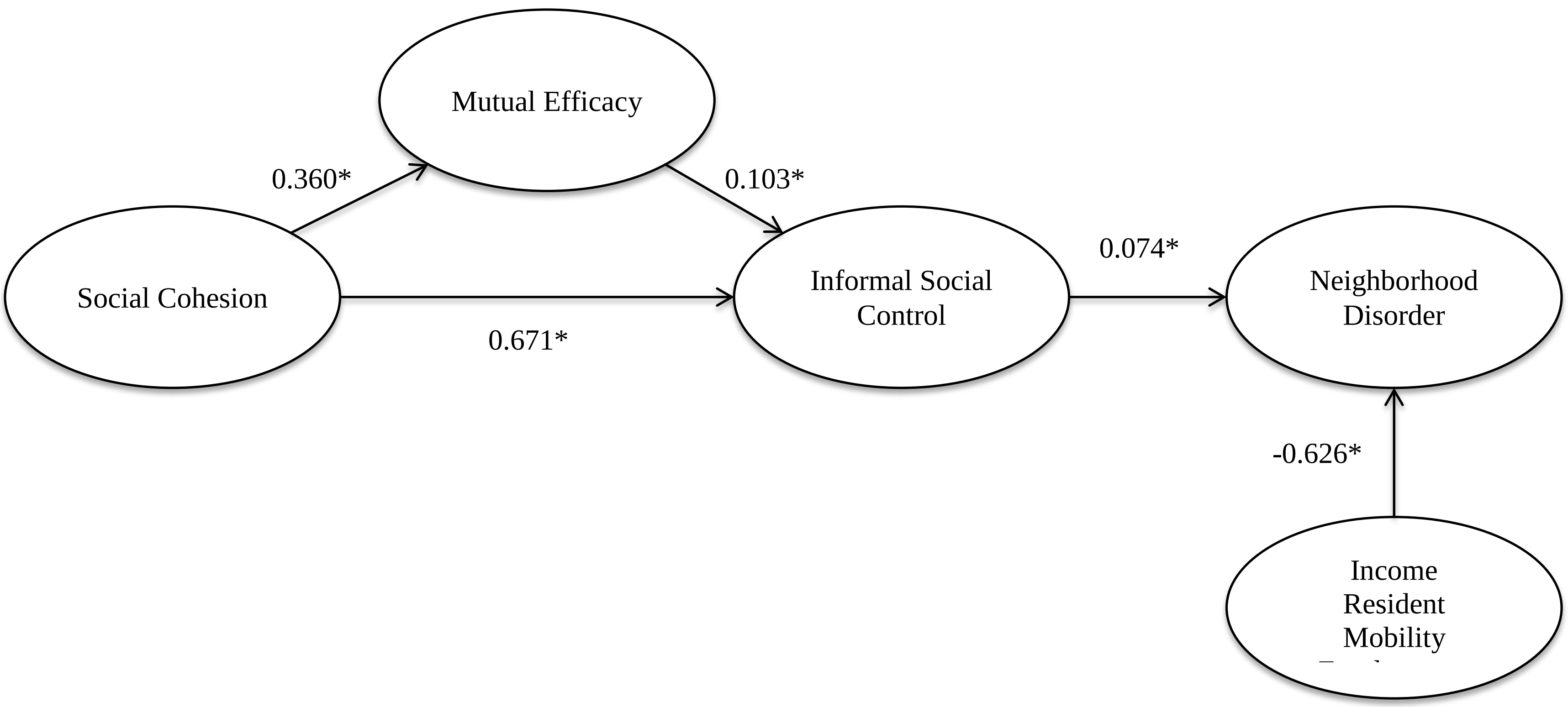
H4: There will be a negative association between mutual efficacy and neighborhood disorder where higher levels of mutual efficacy is associated with lower levels of neighborhood disorder through mutual efficacy's relationship with informal social control.

Statistical analysis: Structural equation modeling

The structural model in Figure 3 provides support for **H4** because informal social control significantly predicted lower levels of neighborhood disorder. A one standard

[3] Because SEM is limited in its ability to include multiple covariates, mutual efficacy model was also estimated using regression controlling for race, age, home ownership, mobility, and income. Findings are not discussed in text because they are consistent with the SEM. A diagram of the regression estimated model can be found in Appendix G.

Figure 3 – Structure Model Results



* $p < 0.05$

deviation increase in informal social control is associated with a 0.074 standard deviation decrease in neighborhood disorder ($p < 0.05$).

Limitations

While the findings of this dissertation are informative, they should be interpreted with care in light of the limitations present in the study. One key limitation of the SNCS is that the original researchers did not calculate weights for the data. This could bias the findings because subgroups of the population may be under or over-represented. This could be a concern as the SNCS sample was older and higher income, had a higher level of education, and were more likely to own their home compared to Census estimates for the city of Seattle. The data were not weighted in this dissertation for two primary reasons. First, the findings are mixed pertaining to the effectiveness of sampling weights on parameter estimates in SEM, particularly with ordinal data (Asparouhov, 2005; Hahs-Vaughn & Lomax, 2006; Kaplan & Ferguson, 1999; Stapleton, 2006). Second, because the purpose of this dissertation is to conduct analyses on the neighborhood level, weights should be assigned to ensure that respondents are representative of their neighborhoods. This is impossible however, because each census tract was assigned a random ID and cannot be linked to Census data. The discrepancies between the SNCS sample and Census estimates may be due in part to landline bias, which typically samples older, higher SES individuals (Fowler, 2004). Further, the city of Seattle has a higher SES compared to many major US cities (Matsueda, 2010). Therefore, the findings presented in this dissertation may not be generalizable to other cities.

The SNCS also contains measures social cohesion and informal social control that differ from the measures developed by Sampson and colleagues (1997). First, the social cohesion and informal social control items are measured using a four-point Likert Scale as opposed to a five-point scale. Further, questions pertaining to social cohesion and informal social control differed from the Sampson et al (1997) measure. Only two items from the original social cohesion measure ("People here are willing to help their neighbors" and "People in this neighborhood can be trusted") were used in the SNCS, and one item from the original informal social control measure ("The fire station closest to their home was threatened to close") was removed from the SNCS. Therefore, the comparisons made in this dissertation are not based on the original measure of collective efficacy developed by Sampson and colleagues (1997).

The SNCS dataset was chosen for this study because it contains two measures that capture the newly developed construct of "mutual efficacy" quite well. The purpose of these items is to reflect whether or not residents believe that the collective actions of residents and neighborhood groups can be successful at achieving goals. While the belief that collective action can be successful is at the core of mutual efficacy, the construct is too complex to be represented by only two items. The items do not include key components of efficacy like the solvability of problems, the ability to reach consensus, and whether or not the community has the ability to work together (Bandura, 2006). Despite these limitations, the measure of mutual efficacy used in this dissertation serves as a useful proxy though it may not represent the entire construct. Unfortunately, the reliability of mutual efficacy could not be calculated because it is only two items.

It is also worth noting that social cohesion, mutual efficacy, and informal social control are typically thought of as neighborhood level concepts. Although the MLCFA was adequately powered to explore the factor structure of these constructs, it was not possible to estimate the paths for the structural model due to power issues. Further, the model cannot determine causality because the data are cross sectional.

Although there is a statistically significant association between informal social control and neighborhood disorder, the relationship between the two is weak. However, sampling and measurement may have an impact on this finding. Respondents may have reported lower levels of neighborhood disorder because the sample was older and of a higher SES than the city of Seattle as a whole. In terms of measurement, informal social control was measured using four items with four response categories whereas neighborhood disorder was measured using five items with three response categories. The conceptual differences between social and physical disorder may have had an impact on this finding as well. Three of the neighborhood disorder items focused on physical disorder and two of the items focused on social disorder. Informal social control may have a stronger relationship with social disorder because it focuses on preventing behaviors that are contrary to social norms. Actions that lead to physical disorder like graffiti may be prevented by informal social control, but pre-existing physical disorder may not be adequately addressed by informal social control. Another possible limitation is that the relationship between informal social control and neighborhood disorder could not be modeled on the neighborhood level using a multilevel structure model due to statistical power. This is a key limitation because neighborhood disorder and informal social control are both neighborhood level constructs and should be modeled on the neighborhood level.

Conclusion – Chapter 5

Despite the limitations described above – the findings presented in this chapter are consistent with prior studies that explore the factor structure of collective efficacy – namely that social cohesion and informal social control are better represented as separate concepts. Mutual efficacy is also supported as partial mediator of the relationship between social cohesion and informal social control. Findings from the structural model suggest that the modified model of collective efficacy where mutual efficacy mediates the relationship between social cohesion and informal social control fits the data better than the current model of collective efficacy, which combines social cohesion and informal social control. The modified model of collective efficacy also predicts lower levels of neighborhood disorder when controlling for income, resident mobility, and employment. The following chapter will discuss the implications of the results presented in this chapter.

Chapter 6 – Discussion and Conclusion

Chapter 6 begins with a general discussion based on the findings presented in Chapter 5. Then the implications of these findings for social work research and practice will be described. The chapter will end with a summary of the conclusions based on the work presented in this dissertation.

Discussion

Collective efficacy is a widely studied predictor of multiple outcomes for communities. Despite being studied by scholars for nearly 20 years, interventions informed by collective efficacy have been limited in their effectiveness. This dissertation attempts to create linkages between social work theory, research, and practice by revisiting our conceptual understanding of collective efficacy. A critique of collective efficacy revealed that the conceptualization of collective efficacy discusses the belief that collective action can be successful at attaining group goals. However, this belief is currently absent in empirical studies. Therefore, the concept of "mutual efficacy" was developed in this dissertation to make this component more explicit, and to study its role as a mediator between social cohesion and informal social control.

A key step in studying mutual efficacy was testing whether or not the construct is distinguishable from social cohesion and informal social control. Nearly all of the evidence from the analyses conducted for this dissertation indicates that social cohesion, mutual efficacy, and informal social control are unique constructs in the Seattle Neighborhoods and Crime Survey (SNCS) sample. The only exception is the high correlation between social cohesion and informal social control on the individual level of the multilevel confirmatory factor analysis (MLCFA). However, the exploratory factor analysis (EFA) and all of the fit indices from the MLCFA indicate that social cohesion and informal social control are unique constructs despite this correlation. The high correlation is most likely due to the fact that social cohesion is a precondition for informal social control. The constructs are separate however, because trusting neighbors and having shared expectations for acceptable behavior is not the same as intervening to enforce social norms. This finding is also consistent with research that supports modeling social cohesion and informal social control as separate factors (Brisson & Altschul, 2011; Wickes et al., 2013). Although Sampson and colleagues (1997) combine social cohesion and informal social control in their empirical work, they describe these constructs as though they are separate (Sampson 2012). Therefore, separating social cohesion and informal social control is consistent with the current conceptualization of collective efficacy.

Mutual efficacy was also found to be a unique construct that partially mediates the relationship between social cohesion and informal social control. Conceptually, social cohesion has been thought of as a social resource that can be drawn upon to bring about collective actions like informal social control (Sampson, 2012). Community members are more likely to enforce social norms if they agree on norms, can identify what constitutes delinquent behavior, and trust other community members to enforce norms (Sampson et al., 1997). However, social cohesion doesn’t always lead to informal social control (Bellair & Browning, 2010). Mutual efficacy can be thought of as an activating agent that increases the likelihood that social cohesion can lead to collective actions like informal social control. If community members don’t believe that their actions will be successful at enforcing social norms, they will be less likely to intervene.

If community members trust one another, have a shared understanding of what constitutes acceptable behavior, and believe that their actions will be successful at enforcing social norms, they will be more likely to intervene when they witness behaviors that are not consistent with the norms of the community. Understanding the factors that lead to collective action can inform practice that empowers communities to create change. However, mediation studies like the one presented in this dissertation were impossible in prior research because collective efficacy was measured by combining social cohesion and informal social control.

Implications for Research

The finding with the most significant implication for future research is that mutual efficacy is a construct that is unique from, but positively correlated to social cohesion and informal social control. Future studies can continue to develop mutual efficacy by creating a more valid and reliable measure of mutual efficacy based on the guidelines described in Chapter 3. Although the measure used in this dissertation reflects respondents' beliefs that collective action can be successful, it fails to incorporate other key aspects of mutual efficacy like the ability to identify problems, the perceived solvability of problems and whether or not the respondent believes that the community has the ability to work together effectively (see Appendix F for a sample mutual efficacy scale).

Future research can explore mutual efficacy's role as a mediator of social cohesion and informal social control in other settings. It is important to test the relationships among social cohesion, mutual efficacy, and informal social control using a sample that is more representative of Seattle as a whole, and more representative of urban areas in other regions of the country. Further, research on mutual efficacy can study mutual efficacy in suburban and rural settings. Such studies will help determine if the findings of this dissertation are generalizable outside of the SNCS sample.

It is also important for future research to study contextual factors that may impact a community's level of mutual efficacy. Because of the correlations found among social cohesion, mutual efficacy, and informal social control, it is expected that many of the factors that influence the current measure of collective efficacy may also impact mutual efficacy. For example, it can be inferred that mutual efficacy is lower in areas with high levels of resident mobility (Sampson et al., 1999). Mutual efficacy may also be lower in Latino neighborhoods because Latino residents are less likely to report observing behaviors associated with community level constructs like social cohesion and informal social control (Almeida et al., 2009; Burchfield & Silver, 2013; Galster & Santiago, 2006).

Race and poverty are expected to have a particularly strong effect on mutual efficacy. Issues like voter disenfranchisement, red lining, mass incarceration, and eminent domain have created a stark racial and economic divide in the United States (Krivo, Washington, Peterson, Browning, Calder, & Kwan, 2013). Institutionalized racism has had a significant impact on communities of color, theoretically resulting in lower levels of mutual efficacy through practices like over-policing and exclusion from civic participation (Ballard, 2014; Gonnerman, 2004; Maton, 2008; Morrow, 2015; Schneider & Robnett, 2015). Race and poverty can also moderate the relationships among social cohesion, mutual efficacy, and informal social control. Racial diversity can lead to decreased interactions among community members (Putnam, 2000). Limited social interaction prevents residents from developing social cohesion. In terms of informal social control, high poverty neighborhoods of color are policed more heavily (Gonnerman, 2004). This can lead to the formation of negative perceptions of the police. Individuals are less likely to participate in informal social control activities if they believe that police are unable to respond to crime in an effective manner (Drakulich et al., 2012; Rose & Clear, 2004; Randol & Gafney, 2014). The impact that race and poverty have on the mutual efficacy model developed in this dissertation can be tested using a multi-group structural equation model (MSEM). MSEMs estimate models across groups (e.g. racial groups) and compares the findings for significant differences across groups (Hoyle, 2012). Such studies can help explore the impact that race and poverty have on mutual efficacy.

Future research can also examine how communities still manage to act collectively despite long histories of disenfranchisement. For example, racial and ethnic minorities have historically had low participation in elections, which can partially be attributed to the belief that nothing will change because their votes do not matter (Ballard, 2014; Morrow, 2015; Schneider & Robnett, 2015). However, racial and ethnic minority voters were critical in the 2008 and 2012 presidential elections of Barack Obama (Schneider & Robnett, 2015). The link of the belief that change can be successful and collective action is made more salient by President Obama's slogan, "Change." Further, tools that disenfranchise individuals like eminent domain are more likely to be used in low-income, communities of color (Lee, 2013). However, the Dudley Street Neighborhood Initiative (DSNI) was able to petition the government to use eminent domain as part of their development efforts (Nagel, 1990). Studying successful collective action efforts can help uncover methods of influencing mutual efficacy in communities that have histories of oppression and exclusion.

Another key implication based on the factor structure supported by the MLCFA pertains to future research using a summary measure of collective efficacy. Social cohesion and informal social control were statistically indistinguishable on the individual level, which may explain the high correlation between these constructs found by Sampson and colleagues (1997) in the PHDCN sample. It may also explain why many researchers continue to combine these constructs into a summary measure of collective efficacy. However, the eigenvalues and factor loadings of the EFA and all fit indices for the MLCFA support treating social cohesion and informal social control as unique concepts. Based on this finding, it is important for researchers to first explore the factor structure of social cohesion and informal social control on both the individual and neighborhood levels prior to conducting other analyses.

Although the MLCFA suggests that social cohesion, mutual efficacy, and informal social control are unique constructs; it cannot be guaranteed that the associations among the constructs are the same on the neighborhood level. This would mean that the mediation model developed in this dissertation varies between neighborhoods. However, it can be reasonably inferred that the relationships tested in this dissertation will be supported on the neighborhood level because multilevel structural equation models tend to be biased towards the findings on the individual level (Byrne, 2012). Further, social cohesion, mutual efficacy, and informal social control are considered to be neighborhood constructs. Therefore, the distinctions between, and relationships among these constructs are thought to occur on the neighborhood level. However, future research should test this structural model with data that have a sufficient number of cases on the neighborhood level before drawing conclusions.

The findings from the structure model showed that mutual efficacy has weaker relationships with social cohesion and informal social control relative to the relationship between social cohesion and informal social control. Future research should examine these relationships with data that addresses the measurement issues discussed in Chapter 5. The structure model also suggests that the mutual efficacy model is limited in its effectiveness in terms of addressing neighborhood disorder in the SNCS data. Future research should also explore the relationship between informal social control and neighborhood disorder and determine if this finding was due to measurement, sampling, or if there are other actions that communities can take that have a stronger impact on neighborhood disorder. As discussed in Chapter 5, there may be statistical limitations that may have impacted the strength of the relationship between informal social control and neighborhood disorder. It is also important to test the mutual efficacy model as it relates to other community outcomes like crime.

Social work research can also explore methods of building mutual efficacy. One method of doing this is to study collective action efforts using quantitative and qualitative methods. For example, interviewing individuals from initiatives like the DSNI can help researchers understand why the initiative started, what were key turning points that fostered a belief that collective action can be successful, and how this belief is maintained over time. Similarly, studying groups that are not place based like the Black Lives Matter Movement can explore whether or not the model of mutual efficacy developed in this dissertation is similar in communities of identity.

Such studies may provide key insights in terms of how and why these communities were able to act collectively, and identify key factors that helped build the community's belief that collective action can be successful. As previously stated, enforcing illegal dumping laws was a critical victory that built momentum for the DSNI (Nagel, 1990). A similar sense of momentum may be building in the Black Lives Matter Movement after prosecutors from Chicago and Cleveland were not re-elected following police abuse controversies (Krayewski, 2016). Studying initiatives that focus on a community's assets like Asset Based Community Development (Kretzman & McKnight 1993) can provide insight in terms of how focusing on assets can increase a community's belief that collective action can be successful. Not only can this vein of research contribute to our understanding of mutual efficacy specifically, but it can contribute to our general knowledge of collective action as well.

Future research can not only continue to examine the role that mutual efficacy plays in facilitating informal social control, but research can also examine additional collective actions like mass demonstrations, civic participation, and participation in change efforts like comprehensive community initiatives (CCIs). Although Sampson (2004) states that collective efficacy does not have to be limited to informal social control, the body of collective efficacy research almost exclusively studies informal social control (for reviews of studies see: Sampson et al., 2002; Sutherland et al., 2013). The lack of research pertaining to the study of social cohesion and other collective actions is most likely due to the fact that informal social control has been an inseparable part of the conceptualization and operationalization of collective efficacy.

Another important step in mutual efficacy research is to study possible relationships with other collective actions and community outcomes. Prior research suggests that social cohesion and informal social control are important predictors of multiple social issues like neighborhood disorder, crime, and physical health. Mutual efficacy is most likely related to these outcomes as well. However, mutual efficacy's relationship with these outcomes can be mediated through multiple mechanisms. For example, this dissertation demonstrated that mutual efficacy is indirectly related to neighborhood disorder through informal social control. It is reasonable to suggest that the relationship between mutual efficacy and informal social control will have a similar impact on crime. Mutual efficacy may be related to other outcomes like physical health through resident participation in community gardens and farmers' markets. Mutual efficacy may also be related to policy change through civic participation activities such as petitions, increasing voter turnout, and political protests. Understanding how mutual efficacy fosters other forms of collective action can increase the utility of collective efficacy for community practice.

Implications for Community Practice

Community level interventions based on the current conceptualization of collective efficacy are limited in their utility because they only focus on improving community outcomes by raising social cohesion and informal social control (Ohmer, 2007; 2008a, 2008b; Ohmer & Beck, 2006; Ohmer et al., 2010). As described in Chapter 1, these interventions typically impact social cohesion and informal social control for a small group of individuals, but fail to increase collective efficacy in the broader community (Ohmer, 2007; 2008a, 2008b; Ohmer & Beck, 2006; Ohmer et al., 2010).

Part of the limited effectiveness of these interventions may be due to the small proportion of community members receiving the intervention, but there are also important conceptual issues to consider.

The current model of collective efficacy can lead to lower levels of mutual efficacy because it does not create a space for community members to be active participants in the change process because informal social control has been chosen as the collective action of interest. However, including the community in identifying action steps is a critical for empowering communities (Maton, 2008). Including mutual efficacy within collective efficacy theory places a greater emphasis on community engagement, participation, and self-determination. This is due to mutual efficacy's conceptual foundation in the empowerment literature, which frames the community as active participants in the change process (Maton, 2008). Further, the current model of collective efficacy does not include the strengths and assets of a community aside from social cohesion. Initiatives based on mutual efficacy frame communities as collectives that can use their strengths and assets to co-create solutions to issues; rather than focusing on a deficiency (violating social norms). Further, focusing on the strengths of a community can increase mutual efficacy because it acknowledges that communities have the power to create change, and places the power to change in the community (Kretzman & McKnight, 1993).

Although informal social control is a predictor of multiple community outcomes (Sampson, 2012), it may not be the most effective action for addressing all issues facing communities. Broadening the scope of collective efficacy to include other forms of collective actions can inform interventions that extend beyond enforcing norms. For example, communities can perform a variety of actions like facilitating mass demonstrations, and civic participation. One possible explanation for the weak impact of CCIs on collective efficacy may be that CCIs attempt to increase resident participation in change initiatives. However, these initiatives focus on many areas that informal social control may not affect like work force development and family services (Kubisch et al., 2010a). Exploring social cohesion's relationship with multiple forms of collective action may help explain why CCIs appear to have a limited impact on collective efficacy despite their generally positive impact on community level outcomes. Social cohesion may predict participation in CCIs and by extension, better outcomes. CCIs are based on multiple actions that can include, but are not limited to informal social control. Therefore, the weak impact of CCIs on collective efficacy may be an issue of measurement.

The mediation model tested in this dissertation also serve as a general framework to guide efforts aimed at facilitating collective action in communities. Social cohesion is a resource that can be built in communities. Raising a community's mutual efficacy can increase the likelihood that residents will act collectively to achieve a variety of community goals like reducing neighborhood disorder. Interventions designed to address social cohesion, mutual efficacy, and informal social control will be described in the following paragraphs.

Interventions targeting social cohesion can focus on establishing connections and facilitating dialogue among community members. Through these interactions, members can build consensus in terms of identifying assets, problems, and creating goals, priorities and action steps to address problems facing the community (Fook, 2002; Hardcastle et al., 2004; Mezirow, 2000; Mezirow & Taylor, 2009). Interventions that target a community's ability to act typically build the capacity and skills required to perform actions. For example, communities that desire to increase informal social control can focus on building skills and knowledge pertaining to conflict management, restorative justice, and peacemaking (Ohmer et al., 2010). Initiatives that focus on policy change can register voters and inform communities about the legislative process.

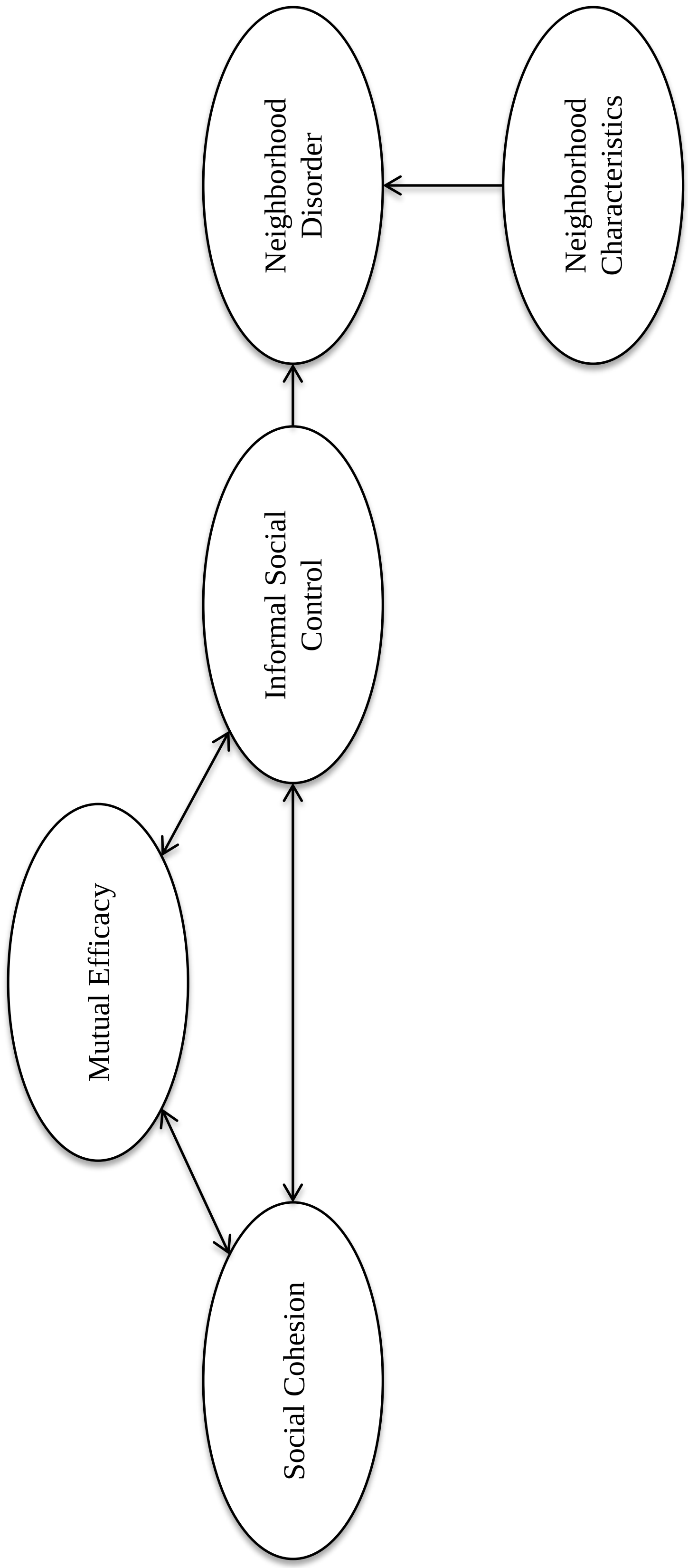
The literature provides multiple ideas of how to build mutual efficacy in communities. Community engagement is critical for building mutual efficacy because the community becomes an active participant in the change process. As described in Chapter 3, building consensus on topics like problems, goals, and action steps can build mutual efficacy. Residents are less likely to believe that their actions can have an impact if they perceive themselves as powerless. Engaging the community, and identifying and mobilizing assets in communities can build mutual efficacy because it relocates the power to create change to within the community as opposed to outside of it (Kretzman & McKnight 1993; Mathie & Cunningham, 2003). Setting realistic goals and achieving small victories early on in the change process can also build mutual efficacy by demonstrating that the community can create change (Hardcastle et al., 2004; Nagel, 1990).

Focusing on the strengths and assets of a community is at the core of mutual efficacy. However, mutual efficacy also presents a risk of overlooking a community's needs. The community may also be blamed for its problems by stating that the primary issue preventing collective action is a community's perception of whether or not collective action can be successful. It is important to engage in research that explores factors that influence mutual efficacy. Mutual efficacy creates an opportunity to identify, discuss, and develop methods of overcoming factors that disempower communities like red lining, voter disenfranchisement, mass incarceration, over policing, and eminent domain. To ignore the impact that these structural factors have on communities is to overlook the root causes of many social issues (Sharkey, 2014). On the other hand, mutual efficacy also creates opportunities to examine why communities can feel empowered despite structural barriers. For example, collective actions generally occur within communities that are the targets of disempowering practices (Hardcastle et al., 2004; Kretzman & McKnight, 1993; Nagel, 1990). Mutual efficacy provides an opportunity to understand structural factors that disempower communities, and can identify methods of empowering communities to create change.

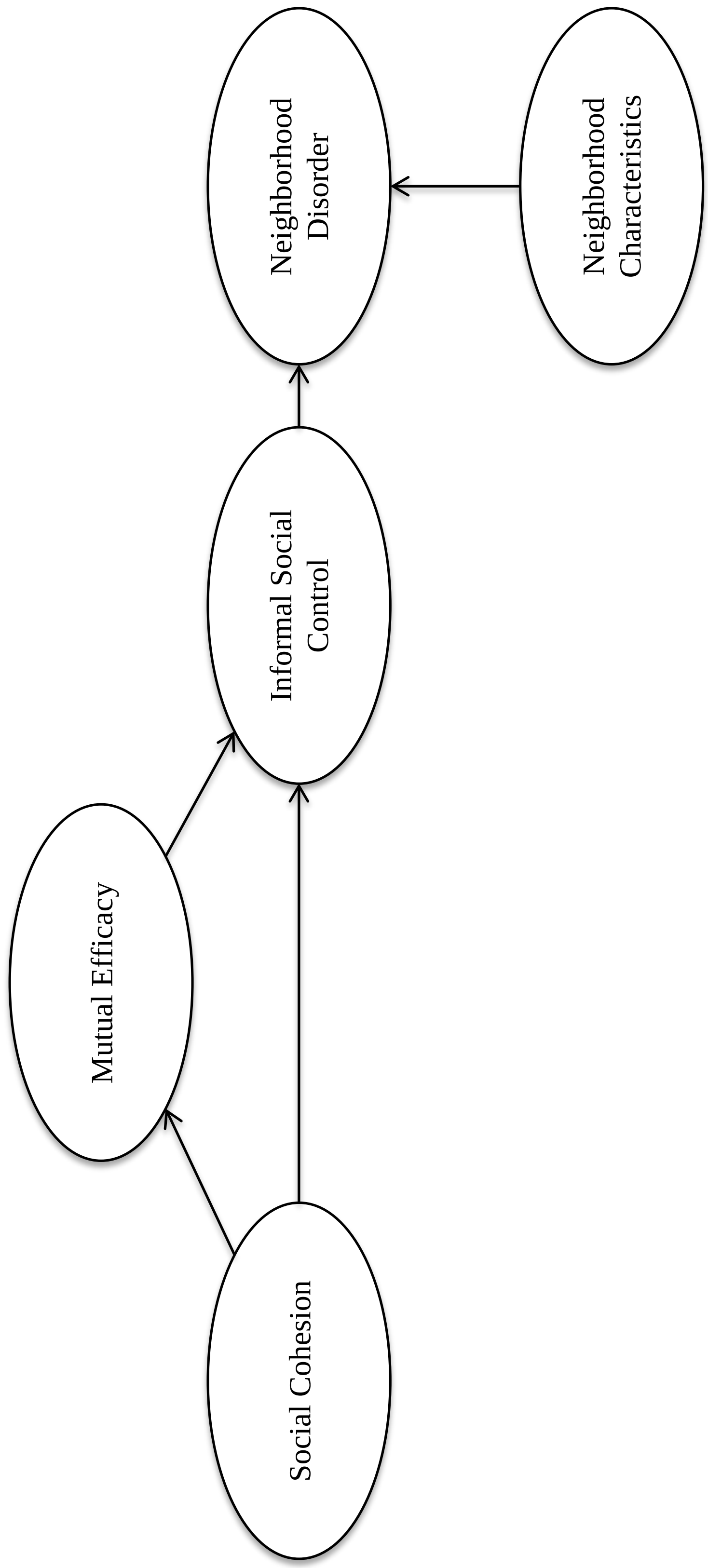
Conclusion – Chapter 6

Collective efficacy has been an important part of community research for the past two decades, and has been supported as a theory that explains and predicts multiple community level outcomes. However, research that focuses on raising collective efficacy suggests that there are gaps between theory, research, and practice. A key question for community practice is how can collective efficacy be modified to better inform community practice. To do this, I developed mutual efficacy to allow researcher to study a construct that was implicit in our understanding of collective efficacy: the belief that collective action can be successful at achieving group goals. Although testing alternative models of collective efficacy is a relatively new phenomenon, findings from this dissertation suggest that mutual efficacy mediates the relationship between social cohesion and informal social control in the SNCS sample. Despite the limitations described in Chapter 5, there is ample evidence to suggest that future collective efficacy research should continue to incorporate mutual efficacy. Research building on this dissertation can help inform interventions aimed at facilitating collective action in communities. The continued study of mutual efficacy's role in collective efficacy theory and practice could help substantially increase the effectiveness of community interventions in improving an array of individual and community outcomes.

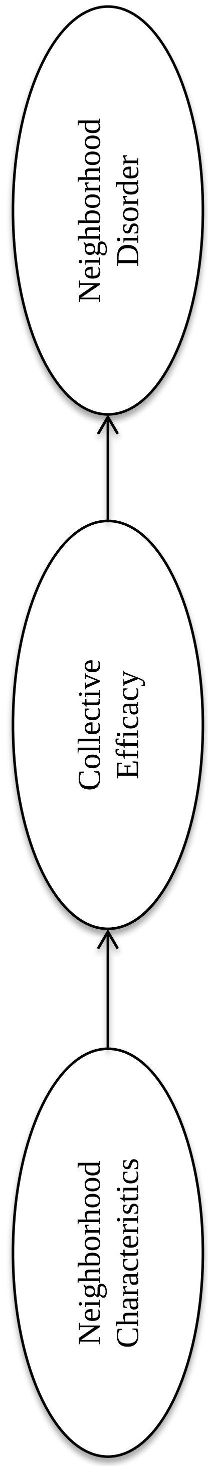
Appendix A – Proposed Model of Collective Efficacy



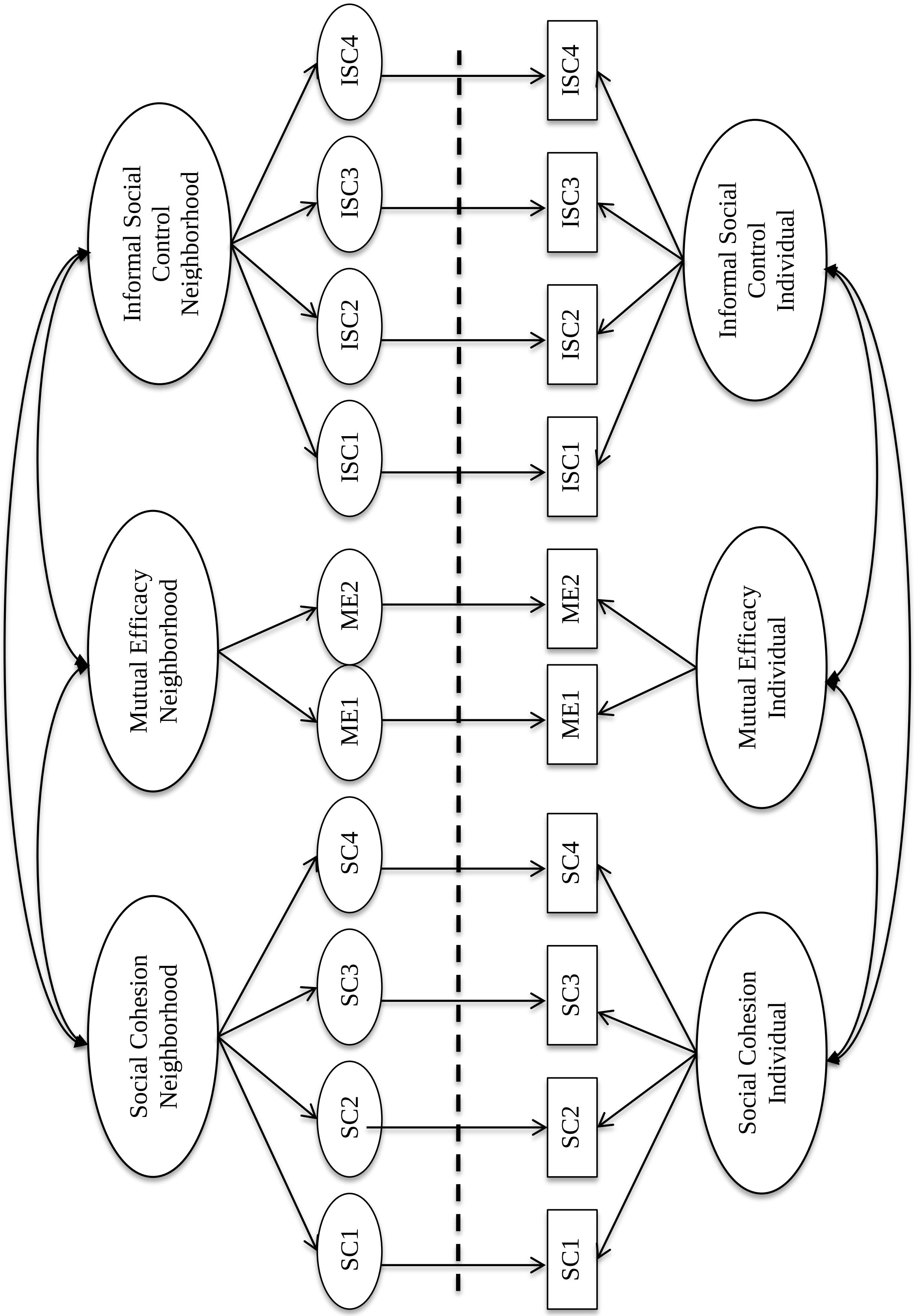
Appendix B – Mutual Efficacy Model



Appendix C – Current Model of Collective Efficacy



Appendix D – Multilevel Confirmatory Factor Analysis



Appendix E – Measures of Collective Efficacy

Sampson, Raudenbush, and Earls (1997)

Social Cohesion

1.) People around here are willing to help their neighbor.

2.) This is a close-knit neighborhood.

3.) People in this neighborhood can be trusted.

4.) People in this neighborhood generally don't get along.

5.) People in this neighborhood do not share the same values.

Responses are recorded on a five-point Likert scale ranging from (1) strongly agree to (5) strongly disagree and items 4 and 5 are reverse coded.

Informal Social Control

Would you say that it is very likely, likely, neither likely nor unlikely, unlikely, or very unlikely that neighbors would intervene if:

1.) Children were skipping school and hanging out on a street corner.

2.) Children were spray-painting graffiti on a local building.

3.) Children were showing disrespect to an adult.

4.) A fight broke out in front of your house.

5.) The fire station closes to your home was threatened with budget cuts.

Responses were recorded on a five-point Likert scale ranging from (1) very likely to (5) very unlikely.

Goddard, Hoy, and Hoy (2000)

1.) Teachers in this school have what it takes to get the children to learn.
2.) Teachers in this school are able to get through to difficult students.
3.) If a child doesn't learn something the first time, teachers try another way.
4.) Teachers here are confident they will be able to motivate their students.
5.) Teachers in this school really believe every child can learn.
6.) If a child doesn't want to learn teachers here give up.
7.) Teachers here need more training to know how to deal with these students.
8.) Teachers in this school think there are some students that no one can reach.
9.) Teachers here don't have the skills needed to produce meaningful student learning.
10.) Teachers here fail to reach some students because of poor teaching methods.
11.) These students come to school ready to learn.
12.) Home life provides so many advantages they are bound to learn.
13.) The lack of instructional materials and supplies makes teaching very difficult.
14.) Students here just aren't motivated to learn.
15.) The quality of school facilities here really facilitates the teaching and learning process.
16.) The opportunities in this community help ensure that these students will learn.
17.) Teachers here are well prepared to teach the subjects they are assigned to teach.
18.) Teachers in this school are skilled in various methods of teaching.
19.) Learning is more difficult at this school because students are worried about their safety.

20.) Drug and alcohol abuse in the community make learning difficult for students here.

21.) Teachers in this school do not have the skills to deal with student disciplinary problems.

Responses are recorded on a six-point Likert scale ranging from strongly agree to strongly disagree.

Benight (2004)

Rate how well you feel your community can handle each situation below *currently*, not as it was the day of the flood or fire.

1.) Ability to quickly coordinate community wide action

2.) Ability to organize how specific demands facing the community will be addressed across the community.

3.) Ability for organizational structure to delegate responsibility to the most appropriate individuals to meet crisis demands.

4.) Ability of community to identify and respond to individuals in greatest need.

5.) Ability of community to recognize the need for outside support.

6.) Effective utilization of outside resources (physical labor, money, food) That are offered.

7.) Ability to adequately solve conflicts within the community.

8.) Ability of community to successfully respond to a future disaster.

9.) Ability for me to work effectively with others in the community.

10.) Ability of me to work with others in the community

11.) Ability to identify appropriate individuals within the community to lead recovery efforts.

12.) Ability of a community to deal with emotional responses that are part of a disaster.

Responses were measured on a seven-point scale ranging from (1) not well at all, (3) not too well, (5) pretty well, and (7) very well.

Appendix F – Sample Mutual Efficacy Scale (MES) Items[4]

Now I am going to ask you some questions about community problems. Tell me how much you agree with the following statements:

People in this area can work together to address its problems.

People in this area can identify the most important problems it is facing.

People in this area can work together effectively in order to address its problems.

People in this area can create a plan to address its problems.

People in this area can identify individuals to lead efforts to solve problems.

People in this area are unable to coordinate actions to solve its problems.

People in this area give up easily.

When problems occur, people in this area do not handle them well.

If problems seem difficult, people in this area will give up.

People in this area cannot organize to address its problems.

People in this area have what it takes to solve its problems.

People in this area are willing to work hard in order to solve its problems.

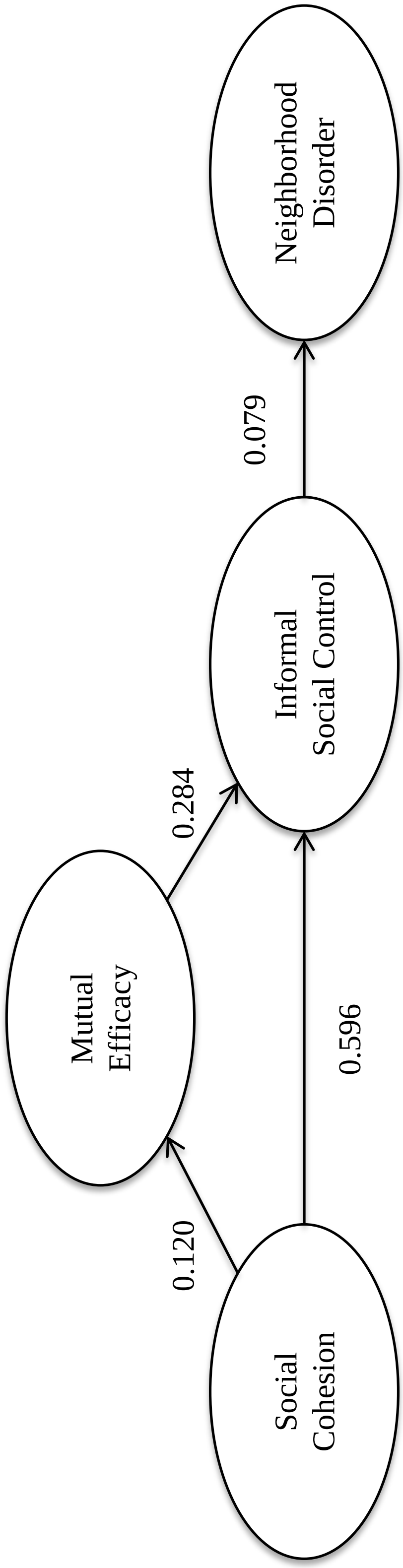
People in this area can carry out a plan to address its problems.

Problems facing this area cannot be solved.

People in this area can solve its problems if we work together.

[4] Responses are recorded using a 5-point Likert scale: (1) strongly agree, (2) agree, (3) neutral, (4) disagree, (5) strongly disagree

Appendix G –Regression Estimated Path Model



* $p < 0.05$

Analyses control for race, age, home ownership, mobility, and income

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