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TOWARDS THE DEVELOPMENT
OF AN INTEGRATED THEORY OF MACRO-LEVEL CRIME:
A MULTILEVEL AND GEOSPATIAL ANALYSIS OF
ANOMIC DISORGANIZATION THEORY

By

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A DISSERTATION

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TOWARDS THE DEVELOPMENT
OF AN INTEGRATED THEORY OF MACRO-LEVEL CRIME:
A MULTILEVEL AND GEOSPATIAL ANALYSIS OF
ANOMIC DISORGANIZATION THEORY

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In recent years, the United States has experienced increasing structural trends of steeply increasing crime rates in some urban neighborhoods and a widening gap in wealth and income inequality between social classes. The primary criminological theory applied to explain neighborhood crime rates is social disorganization theory, while the primary theory linking economic inequality to crime outcomes is institutional anomie theory. However, while there is an increasing trend in the literature towards integrating current theoretical perspectives to better explain macro-level crime, no integrated theoretical frameworks have been developed to explain neighborhood crime patterns applying social disorganization theory at the neighborhood-level and institutional anomie theory at the county-level. Yet, there are many points at which integration of these perspectives is possible and plausible. This dissertation contributes to the literature by first testing social disorganization theory with a nationally-representative sample of 9,593 neighborhoods and then conducting the largest sub-national test of institutional anomie theory to date with data from all 3,142 counties in the United States. Additionally, it contributes by developing and empirically testing an integrated theory of macro-level crime with a multilevel model of 9,365 neighborhoods nested within 83 urban U.S. counties. Finally, geospatial analysis methods are used to examine how social disorganization theory operates at the neighborhood-level in three cities characterized by low, moderate and
high levels of economic inequality. The findings provide a comprehensive assessment of the effects of economic inequality on crime rates and show that strong noneconomic social institutions moderate this criminogenic effect. They also suggest that social disorganization and institutional anomie theories are supported with large, representative samples of neighborhoods and counties, and demonstrate that the proposed integrated theory receives tentative support when subjected to empirical testing.
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Chapter 1: Introduction

In this chapter, I first discuss the purposes and contributions of this dissertation to the body of scholarly knowledge and society more broadly. Second, I briefly outline the fundamental elements of social disorganization theory and institutional anomie theory. Third, I explain the key components in the development of an integrated model of macro-level crime in the United States that I name the anomic disorganization theory. Fourth, I introduce the specific theoretical, substantive and methodological arguments for the integrated anomic disorganization theory, which are explained in greater detail in Chapter 2: Background.

1. Purpose Statement

Among industrialized, developed countries, the United States has one of the highest rates of fatal violent crime, with over 14,000 homicides in 2014 alone\(^1\) (FBI 2015; World Bank 2016). Recent research has demonstrated that homicide rates in some neighborhoods (and their respective counties) in many U.S. cities have increased in 2014 and 2015, after declining for the past two decades (Davey and Smith 2015; FBI 2015; James 2015). Moreover, American society has experienced recent trends in the past two decades of increasing social and economic inequality (Lin and Tomaskovic-Devey 2013; Ryscavage 2015; Kwon 2016), and more recently, a rise in high-profile fatal police use of force among minorities in economically disadvantaged communities (Davey and Smith 2015; Koper 2016). As a result, there has been increased public, political and scholarly attention directed towards neighborhood crime patterns and the negative consequences of

\(^1\) To provide a cross-national perspective, the average homicide rate for the United States was 4 (2011-2015) per 100,000, residents, compared with 1 or less per 100,000 residents for the same period in Australia, Germany, Italy and the United Kingdom, respectively (World Bank 2016).
high levels of economic inequality on social phenomena such as crime rates (Hicks and Hicks 2014; Porter 2014; Stucky, Payton and Ottensmann 2015; Kang 2016).

These recent structural changes in neighborhood crime patterns and social stratification dynamics parallel the concurrent trend of increasing scholarly attention directed towards integrated theories of crime in the past two decades (e.g., Laub 2001; Colvin, Cullen and Vander Ven 2002; Agnew 2003; Tittle 2004; Wikström et al. 2012; Rorie 2015; Antonaccio et al. 2015). However, no integrated theoretical model has been developed and empirically evaluated\(^2\) that simultaneously tests correlates of crime rates at the neighborhood-level with measures of economic inequality and the strength of commitment to noneconomic social institutions at the county-level. Therefore, this dissertation seeks to fill these substantial gaps in the literature.

Patterns of crime are distributed unevenly across geographic units (e.g., neighborhoods, cities, counties and states) and a large body of sociological and criminological research seeks to explain spatial heterogeneity in crime rates at the macro-level (see Pratt and Cullen 2005 for a meta-analysis). Two major theories\(^3\) have been developed to explain variation in macro-level crime patterns: Social disorganization theory (Shaw and McKay 1942) and institutional anomie theory (Messner and Rosenfeld 2001). In short, social disorganization theory argues that neighborhoods with an inability of residents to control crime and disorder, in communities with high levels of structural

\(^2\) More specifically, few tests of other integrated theories of crime such as Wikström et al.’s (2012) situational action theory have used variables from social disorganization theory to measure neighborhood context. Yet, no specific empirical tests using predictors from specific theories at the levels specified in this dissertation have been conducted.

\(^3\) While several other major macro-level theories of crime exist such as routine activity theory, relative deprivation theory, subculture of violence theory and Merton’s (1938) classical anomie theory (Pratt and Cullen 2005), the foci in this dissertation are social disorganization theory and institutional anomie theory.
indicators of social disorganization, are more likely to have higher crime rates (Shaw and McKay 1942). Institutional anomie theory argues that a strong cultural emphasis placed on monetary success in the U.S., combined with a lack of legitimate means to pursue this institutionalized success goal for many people and a weak commitment to noneconomic institutions, results in higher crime rates across ecological units (Messner and Rosenfeld 2001). Key variables from both theories have received moderate to strong support across studies, according to Pratt and Cullen’s (2005) meta-analytic review. Empirical research on social disorganization theory consistently finds that higher levels of the structural factors of residential instability, economic disadvantage and racial/ethnic heterogeneity in neighborhoods are associated with higher crime rates (Sampson, Raudenbush and Earls 1997; Veysey and Messner 1999; Kubrin and Weitzer 2003; Pratt and Cullen 2005). Furthermore, tests of social disorganization theory find that neighborhood-level informal social control, friendship network ties, organizational membership (Sampson and Groves 1989) and the willingness of neighborhood residents to intervene when witnessing suspicious community activity also reduce neighborhood crime rates (Sampson 2012).

For institutional anomie theory, partial tests have shown that larger geographic units (e.g., counties, states and countries) with greater economic dominance (i.e., inequality) and weak commitment to noneconomic social institutions—including the education system, family, community, religious institutions and polity—have higher crime rates (Messner and Rosenfeld 1997; Salvolainen 2000; Pratt and Godsey 2003; Baumer and Gustafson 2007; Bjerregaard and Cochran 2008). More recent empirical tests have also found that a greater commitment to noneconomic institutions mediate (Maume and Lee 2003) and moderate (Maume and Lee 2003; Baumer and Gustafson 2007) the
positive relationship between economic inequality and crime rates. However, empirical findings have been inconsistent, only few studies have tested all concepts in the theory across ecological units within a single nation (Chamlin and Cochran 1995; Piquero and Piquero 1998; Maume and Lee 2003; Baumer and Gustafson 2007) and all extant studies used small, non-representative samples with low statistical power (Cohen 1992).

While both social disorganization and institutional anomie theories receive considerable empirical support, both approaches independently explain only between 10 and 50 percent of the variation in crime rates, leaving the remaining 50 percent or more unaccounted for by any current model (Pratt and Cullen 2005). In addition, researchers have called for more research to be conducted on social disorganization theory at the neighborhood-level with diverse samples and within different macro-level structural contexts (Kubrin and Weitzer 2003). Moreover, researchers also recommend that future tests of institutional anomie theory utilize larger, more representative samples and use novel indicators to operationalize the dominance of the economy and strength of commitment to noneconomic institutions with greater validity and reliability (Baumer and Gustafson 2007; Messner, Thome and Rosenfeld 2008). Therefore, this dissertation seeks to address the current macro-level social changes and to fill these gaps in the extant literature and to advance the scholarly research on integrated theories of crime in the United States. Specifically, this dissertation will: 1) provide an independent test of social disorganization theory with a nationally-representative sample of 9,593 neighborhoods in the United States, 2) provide an independent test of institutional anomie theory with a full census of all 3,142 counties in the United States, and finally, 3) jointly test both theories
together in a newly-developed integrated theoretical framework\textsuperscript{4} named the anomic disorganization theory.

2. Contributions

This dissertation makes several substantial contributions to the literature. These include contributions to social disorganization theory, macro-level anomie theory, neighborhood-level and county-level crime research, methodological applications of multilevel modeling and geospatial analysis techniques, and finally, on the development and empirical testing of the novel anomic disorganization theory. A significant gap in the literature exists in the development of a comprehensive, integrated, multilevel and interdisciplinary theoretical model of crime in neighborhoods simultaneously testing social disorganization theory at the neighborhood-level and institutional anomie theory within larger geographic units (i.e., counties) in which these neighborhoods are located. The proposed anomic disorganization theoretical model developed in this dissertation is tested with representative data on 9,365 neighborhoods in 83 metropolitan counties in the United States from the National Neighborhood Crime Study (Peterson and Krivo 2000) and county-level measures from nine secondary data sources to develop novel measures of key variables from institutional anomie theory and to empirically test social disorganization theory and institutional anomie theory jointly with neighborhood-level violent and property crime outcomes.

First, I use negative binomial regression models to test each theory independently (Long 1997; Osgood 2000) and multilevel modeling techniques (Raudenbush and Bryk

\textsuperscript{4} This dissertation refines and builds on preliminary ideas originally introduced in a previous work by Louderback (2015) in which the term anomic disorganization theory was developed and potential avenues for theoretical integration were discussed.
2002; Luke 2004; Rabe-Hesketh and Skrondal 2012) to test both theories jointly. Second, I use geospatial analysis methods, including local indicators of spatial autocorrelation (i.e., clustering of “hotspots”) and geographically weighted regression (Andresen 2006; Anselin, Syabri and Kho 2006), to demonstrate how neighborhood-level social disorganization and crime rates vary in three cities with different (i.e., low, moderate and high) levels of economic inequality. Based on these findings, I further develop the integrated theory of macro-level crime with theoretical, substantive and methodological justifications, demonstrate its relevance for criminal justice policymakers and show more broadly how structural economic and institutional characteristics of counties affect the neighborhoods located within them.

The present dissertation advances scientific knowledge in three specific ways. First, the current body of research on neighborhood crime patterns is limited because it only applies theories independently and explains a maximum of 50% of the variation in crime, leaving the remaining 50% or more unexplained (Pratt and Cullen 2005). This study integrates current theoretical perspectives to increase the explained variance and produces a more comprehensive theoretical model that can calculate precisely how much of the variation in neighborhood crime is attributable to neighborhood and county-level predictors from each theory. Second, this study is the first to use data from 9,365 neighborhoods in 83 counties that is nationally representative of metropolitan neighborhoods in the United States. This approach is in contrast to previous research that only independently tested either social disorganization theory or institutional anomie theory with smaller samples of either neighborhoods (e.g., a sample of neighborhoods in
Third, this study is one of the first to use multilevel modeling techniques (Raudenbush and Bryk 2002) with smaller geographic units nested within larger geographic units (also see Peterson and Krivo 2009; Ramey 2013), an extension of the traditional nested model of individuals within a larger social context such as a school or neighborhood (Luke 2004). This general methodological approach can be extended to study diverse, interdisciplinary macro-level social phenomena that occur at multiple levels across disciplines, such as concurrently testing the effects of county-level socioeconomic measures and state-level health care expenditures on county-level health outcomes, or jointly testing how neighborhood-level social welfare spending and city-level political mobilization affects neighborhood-level household income inequality.

The current study will benefit society and contribute to the achievement of specific, positive societal outcomes in two ways. First, the development of an integrated theoretical model of macro-level crime provides academic researchers and policymakers with a more complete explanatory model to develop crime control and prevention programs. In particular, the findings identify which variables are the strongest predictors of neighborhood crime, how these factors interact with other variables (e.g., if residential instability is a stronger predictor of crime in counties with high levels of economic inequality or weak commitment to noneconomic institutions), and most importantly, which specific U.S. neighborhoods and counties have the greatest need for targeted interventions to reduce crime rates.
Second, this study examines the potential consequences of economic inequality within counties (and three cities in the geospatial analyses) on crime in neighborhoods in order to determine whether social disorganization theory operates differently with high levels of inequality. Contingent on the findings, society can benefit by developing specific interventions to reduce economic inequality (e.g., more scholarships for low socioeconomic students, increased job training programs and/or more government welfare funding for underprivileged families). These programs in turn could lead to reductions in levels of neighborhood crime and less personal, social and economic hardship among individuals and families in communities.

3. Development of an Integrated Theory of Macro-level Crime

The current state of American society and the lack of research on integrated theories of macro-level crime demonstrate the need for the development of a new perspective integrating social disorganization theory and institutional anomie theory. Prior to developing and empirically testing the integrated theory, I test each theory individually. Social disorganization theory is tested with a nationally-representative sample of 9,593 urban neighborhoods in the United States from 1999-2001 while institutional anomie theory is tested with data from all 3,142 counties in the United States from the same time period.

The move towards theoretical integration is conducted based on theoretical, substantive and methodological grounds. First, each theory and its empirical support is reviewed and then synthesized to specify how main elements of social disorganization theory can be integrated with key concepts from institutional anomie theory. Social disorganization theory operates at the neighborhood level and institutional anomie theory
operates at the county level. I hypothesize that measures of the institutional balance (i.e., the dominance of the economy and strength of commitment to noneconomic institutions) will condition the effects of social disorganization concepts on crime at the neighborhood level. Second, the conceptual and logical linkages are further developed by postulating the specific direct and conditioning effects of variables from institutional anomie theory on variables from social disorganization theory. Moreover, the processes through which institutional anomie influences neighborhoods subsumed within counties is explained by identifying and describing the intervening concepts of social cohesion, social control and social support, which I hypothesize will mediate the effects of institutional anomie measures on social disorganization measures.

More specifically, I hypothesize that counties with a highly dominant economy and a weak commitment to noneconomic institutions will have lower levels of social cohesion, social control and social support in neighborhoods located within those counties. As a result, the criminogenic effects of social disorganization measures will be amplified or more pronounced (i.e., a positive interaction/moderation effect) in these neighborhoods. In contrast, the criminogenic effects of social disorganization measures will be attenuated or less pronounced (i.e., a negative interaction/moderation effect) in neighborhoods nested within counties in which the economy is not the dominant institution and where there is a strong commitment to noneconomic institutions, and in turn where levels of social cohesion, social control and social support are high.

Finally, the move towards an integrated theory is also justified on substantive and methodological bases. Specifically, I argue that my proposed integrated anomic disorganization theory contributes substantively because it: 1) explains a greater
proportion of the variation in crime rates in neighborhoods than existing theories independently, 2) addresses the potential effects of an increasingly dominant economy on neighborhood crime as economic inequality increases in the U.S., 3) applies to both neighborhood-level property and violent crime outcomes and explains the specific processes that contribute to each type of crime, 4) provides criminal justice policymakers and law enforcement agencies with diverse avenues for targeted interventions at multiple levels of municipal government (i.e., in communities and in counties) and, 5) postulates the intervening mechanisms of macro-level social cohesion, social control and social support which link the two theories together to inform future scholarly research.

Furthermore, the proposed empirical evaluation of the integrated theory of macro-level crime also contributes methodologically. This is because it: 1) partitions the percentage of the variance in neighborhood crime rates attributable to neighborhood-level and county-level factors to determine which is more influential; 2) tests social disorganization theory in three cities with low, moderate and high levels of economic inequality (i.e., different levels of economic dominance) with geospatial analysis methods, including local indicators of spatial autocorrelation and geographically weighted regression, to test how social disorganization theory operates with varying levels of inequality; 3) shows how multilevel modeling techniques can be extended to ecological research on crime and social phenomena in nested structures instead of only individual people nested within larger social contexts; 4) develops new measures for institutional anomie concepts of the dominance of the economy and the strength of commitment to noneconomic institutions to guide future research on the theory; and, 5) exemplifies how macro-level researchers can integrate across disciplines and data sources
to develop novel measures and methodological approaches to test existing theories independently and jointly. Each of these contributions is explained in greater detail in the next chapter, and they are reviewed in the discussion based on the results from the empirical testing of the proposed anomic disorganization theory.

In summary, in this chapter, I briefly described the purposes and contributions of this dissertation, identified the theoretical frameworks of social disorganization theory and institutional anomie theory, explained the reasoning for developing an integrated theory of neighborhood crime, and lastly, outlined the key arguments for the proposed integrated theory named anomic disorganization theory. In chapter 2, I review and synthesize the theoretical background and empirical support for social disorganization and institutional anomie theories, describe current approaches to theoretical integration in criminology, detail the theoretical, substantial, and methodological arguments for anomic disorganization theory, and finally, list the research questions and hypotheses which are tested in this dissertation.
Chapter 2: Background

In this chapter, I first discuss the theoretical frameworks of social disorganization theory and institutional anomie theory, including a review and synthesis of the seminal articles in the literature and recent empirical research on each theory. Second, I review the literature on the procedures and processes in theoretical integration in research on crime and delinquency. Third, I outline the key concepts and theoretical linkages in the anomic disorganization theory, describe how this dissertation integrates across methodologies and disciplines, and explain the theoretical, substantive and methodological contributions of the multilevel model of anomic disorganization theory. Finally, I list the research questions and hypotheses that are tested in this dissertation.

1. Theoretical Framework and Literature Review

   a. Social Disorganization Theory

   Social disorganization theory is the oldest and best supported among ecological theories of crime, a class of theories that focus on explaining crime rates at the macro-level (i.e., across neighborhoods, counties, states and/or countries) instead of crime at the micro-level (i.e., across individuals) (Shaw and McKay 1942; Kubrin and Weitzer 2003; Pratt and Cullen 2005). The general definition of social disorganization is the inability of local communities to realize the collective values of their residents or to solve commonly experienced problems (Kornhauser 1978:63; Bursik 1988:521; Bursik and Grasmick 1993). Since highly socially disorganized communities are unable to realize their common values and encounter difficulties in working together to solve commonly experienced problems (e.g., to be free of property and violent victimization), these neighborhoods tend to have higher crime rates than communities with low levels of social
disorganization (Kornhauser 1978; Sampson 2012). The social disorganization theory of crime was developed by University of Chicago urban sociologists Shaw and McKay (1942) to explain differences in juvenile arrests in concentric zones of Chicago, characterized by varying levels of socioeconomic and demographic variables. Shaw and McKay (1942) plotted juvenile and adult arrests in the Chicago metropolitan area over time and discovered that certain areas within what that they deemed the “zone of transition” had consistently high rates of crimes and arrests regardless of the particular racial and ethnic groups residing in those areas. Furthermore, they found that certain areas, including the “commuter zone” and “central business district” in the core of the city, had lower crime rates and arrests over time, again despite the sociodemographic composition and characteristics of the individual residents living there (Shaw and McKay 1942).

After studying these data in detail, Shaw and McKay (1942) concluded that structural, ecological characteristics of neighborhoods affect crime rates within them and that three macro-level variables were the best predictors of higher levels of neighborhood crime. Specifically, they found that neighborhoods with high levels of residential instability, economic disadvantage and ethnic/racial heterogeneity have higher crime rates because of a breakdown in social control among residents which results in the inability to control crime in one’s neighborhood (Kornhauser 1978). Residential instability refers to neighborhoods with more renters (vs. owners) and greater transiency in residential housing patterns over time. Economic disadvantage⁵ pertains to

⁵ For each of these structural indicators, the examples provided are common conceptualizations; however, other measurement approaches have been used (see Pratt and Cullen 2005; Kubrin and Weitzer 2003; Sampson 2012).
communities with low levels of income and wealth among residents. Finally, ethnic/racial heterogeneous (vs. homogeneous) neighborhoods are comprised of diverse ethnic and racial groups residing in close proximity to each other within the same community (Shaw and McKay 1942; Kornhauser 1978).

Most importantly, Shaw and McKay (1942) argued that increasing levels of these three structural factors reduced community social control processes. In this context, social control is defined as behaviors of neighborhood residents that bring about conformity with laws and collectively reduce crime. These behaviors include, for example, “neighbors questioning strangers, watching over each other’s property and intervening in local disturbances” (Greenberg, Robe and Williams 1985:2). Thus, the inability to collectively control neighborhoods informally by intervening in disorder and crime when it occurs (i.e., informal social control) or by calling law enforcement (i.e., formal social control) results in higher neighborhood crime rates (Bursik and Grasmick 1993).

The social disorganization theory of crime fell out of favor in the scientific community between the 1960s and early 1980s due to a focus on individual-level theories and survey research (see Kornhauser 1978; Kubrin and Weitzer 2003). Kornhauser’s (1978) seminal book provided a criticism of the current state of macro-level theories of crime and also spurred a resurgence of interest in social disorganization theory that motivated future work in the area. Within her critique, Kornhauser (1978:253) constructed an analytic typology of theories of crime into control, strain and cultural deviance models, and she was highly critical of the latter as “so abused…in the
explanation of delinquency that…the study of delinquency would benefit from their absence.”

One of her most important contributions to social disorganization research was in identifying the theory as a control theory. Kornhauser (1979) saw the source of neighborhood crime as not based on the necessity of criminal subcultures entirely opposed to mainstream and conformist culture, but instead due to the weakening of conventional or normative culture and the resulting lack of informal control which increases crime rates (Kornhauser 1978). Overall, Kornhauser’s (1978) work refocused scholarly interest on empirically testing social disorganization and led to greater emphasis placed on the measurement of the control aspects of the theory, including informal social control and social ties, and later social capital and collective efficacy, perspectives which have been developed over the past three decades6.

Drawing from Kornhauser’s (1978) seminal work, social disorganization was further revitalized by studies such as those by Bursik (1988), Sampson and Groves (1989) and Bursik and Grasmick (1993). These studies focused on the intervening concepts of social control and social ties in the social disorganization and crime relationship. Bursik’s (1988) theoretical commentary draws from Kornhauser’s (1978) focus on control mechanisms and Stark’s (1987) theoretical focus on an ecological theory of crime. Bursik (1988) identified five major criticisms and three new directions of the theory, and most importantly, clearly delineated the three intervening mechanisms by which residential

6 While more recent empirical tests of social disorganization theory have used direct indicators for intervening concepts such as collective efficacy (Sampson, Raudenbush and Earls 1997; Sampson 2012), the social control processes are assumed to be reduced as structural measures social disorganization increase. See Kubrin and Weitzer (2003) for more details on conceptual and measurement issues in social disorganization research.
instability and population heterogeneity increase neighborhood crime rates. The
criticisms of the theory that Bursik (1988) reviews include: 1) the disciplinary shift in
criminology towards focusing on individual behaviors, 2) the assumption of stability in
ecological structures, 3) inconsistencies in study methodologies and the
operationalization of social disorganization concepts, 4) issues in the validity of
measurement of neighborhood crime and delinquency, and 5) the normative assumption
that communities seek social organization and consensus. To remedy these shortcomings,
Bursik (1988) delineates three extensions of social disorganization theory, including
identifying the neighborhood as a context for individual behavior, combining both crime
outcomes and victimization outcomes to better test social disorganization and testing for
reciprocal relationships between social disorganization and crime, such that crime may
also affect future levels of community control.

Of the major points raised by Bursik (1988), the two most important for the study
of social disorganization are the three intervening mechanisms through which social
disorganization increases neighborhood crime and the recognition of contextual effects of
neighborhood-level variables on the individuals within them. Specifically, the three
intervening processes described by Bursik (1988) that laid the groundwork for future
studies include: 1) the inability of informal social control processes to manifest among
residents who desire to leave the community if and when possible (i.e., residential
instability $\rightarrow$ low informal social control $\rightarrow$ crime), 2) the lack of development of strong
interpersonal relationships to foster informal social control due to consistent population
turnover and transiency (i.e., economic disadvantage and residential instability $\rightarrow$ lack of
social ties $\rightarrow$ low informal social control $\rightarrow$ crime), and 3) lack of communication and
personal interaction among diverse cultural and linguistic populations preventing achievement of common goals and solving community-wide problems (i.e., population heterogeneity → reduced local friendship networks and organizational participation → crime). Finally, Bursik’s (1988) identification of the importance of situating individuals in the neighborhood context and for testing for contextual factors informed future primary data collection such as the Project in Human Development in Chicago Neighborhoods (PHDCN) and seminal studies such as Sampson, Raudenbush and Earls (1997) that developed the concept of collective efficacy. The development of multilevel methodologies also made possible these and additional studies of individuals within the neighborhood context (Raudenbush and Bryk 2002).

Sampson and Groves (1989) built on Bursik’s (1988) theoretical piece by conducting the first empirical test of social disorganization theory that explicitly operationalized and tested for the effects of measures of social disorganization and intervening variables. Using data from two samples from Great Britain from the British Crime Survey, the first with 10,905 respondents in 238 geographic regions in 1982 and the second with 11,030 respondents in 300 geographic regions in 1984, Sampson and Groves (1989) found support for the direct effects of social disorganization variables and intervening factors of informal social control, local friendship networks and organizational participation on criminal offending and victimization. More specifically, Sampson and Groves (1989) concluded that a large proportion of the effects of the exogenous structural characteristics of social disorganization (i.e., economic disadvantage, residential instability and population heterogeneity) were mediated by measures of sparse friendship networks, unsupervised peer groups and low organizational
participation in communities, which in turn significantly predicted higher levels of neighborhood crime. The authors conclude by suggesting that “social disorganization theory has vitality and renewed relevance for explaining macro-level variations in crime rates” and that its empirical support in a new geographic region of England and Wales enhances its generalizability outside of the United States (Sampson and Groves 1989:799).

Bursik and Grasmick’s (1993) influential book entitled *Neighborhoods and Crime: The Dimensions of Effective Community Control* also strengthens the case for the testing of the revised “systemic” model of social disorganization. It further develops the theoretical and empirical typology of social control into three domains drawing from Hunter (1985): Private control, parochial control and public control. Much like Kornhauser (1978), they eschew cultural deviance models, instead focusing almost exclusively on the application of a model that links intra-community control mechanisms (e.g., informal social control and social ties) to extra-community control mechanisms (e.g., formal government and law enforcement control), with outcomes including offending, gang participation, fear and victimization by crime and targeted crime prevention strategies.

Within Bursik and Grasmick’s (1993) tripartite typology of control, private control is fostered and enacted by families and close friends through social support mechanisms. Public control is exercised by the “formal, bureaucratic agencies of the state” (Hunter 1985:234) and “focuses on the ability of the community to secure public goods and services that are allocated by agencies located outside of the neighborhood” (Bursik and Grasmick 1993:17). Parochial social control falls between these two
extremes, and it pertains to the social control exercised by the supervision of neighborhood behaviors within local social networks and voluntary social organizations and community institutions such as churches and schools. Furthermore, Bursik and Grasmick (1993) argue for the development of more valid and reliable measures of the structural and intervening concepts in social disorganization theory and posit that the revised, systemic model of social disorganization has great promise to guide future research on neighborhood crime patterns. The most important contributions of this work are the increased focus placed on refining the measurement of the intervening concepts in the systemic social disorganization model including informal and formal social control, social ties and institutional involvement, and the call for more valid and reliable measurement with innovative methodologies. These approaches have been successfully applied in more recent work on social disorganization theory (Kubrin and Weitzer 2003).

Social disorganization has been further developed in recent years by Sampson, Raudenbush and Earls (1997) and Sampson (2012), primarily due to the development of innovative research methodologies such as multilevel modeling and social network analysis and new datasets such as the Project in Human Development in Chicago Neighborhoods (PHDCN). First, Sampson, Raudenbush and Earls (1997) built on previous work such as Sampson and Groves (1989) by investigating the intervening mechanisms of informal social control and social ties with the newly-developed methodological technique of multilevel modeling (developed in 1992; Raudenbush and Bryk 2002) to develop the novel concept of collective efficacy. Collective efficacy integrates the concepts of informal social control and social cohesion; it is defined as “social cohesion among neighbors combined with their willingness to intervene on behalf
of the common good” (Sampson, Raudenbush and Earls 1997:918). The authors note that while a large body of previous research has consistently found that neighborhood characteristics including economic disadvantage, residential instability and population heterogeneity predict increased crime rates, few studies have investigated the mediating mechanisms in this relationship. Therefore, they conclude that beyond the ecological correlates of crime and violence from social disorganization theory, “the differential ability of neighborhoods to realize the common values of residents and maintain effective social controls is a major source of neighborhood variation in violence” (Sampson, Raudenbush and Earls 1997:918).

To test their hypotheses, Sampson, Raudenbush and Earls (1997) use PHDCN data from 8,782 residents nested within 343 neighborhoods in Chicago, Illinois from the year 1995. This dataset includes measures of economic disadvantage, residential instability and population heterogeneity at the neighborhood-level and a measure of collective efficacy, which combines a measure of social cohesion and a measure of informal social control collected at the individual-level that was aggregated up7 to the neighborhood-level. Using multilevel models to control for measurement error and individual-level characteristics, they found that 70% of the variation in collective efficacy was explained by the three structural social disorganization measures, that a large portion of their effects on violence were mediated by collective efficacy, and that collective efficacy was negatively associated with all violence outcomes. Finally, when controlling for intervening concepts in the systemic social disorganization model including

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7 In this study, Sampson, Raudenbush and Earls (1997) construct neighborhood-level measures of social cohesion and social control by averaging the individual-level survey responses for all residents sampled in each neighborhood. In addition, they use statistical techniques described in Raudenbush and Bryk (2002) to reduce measurement error and potential biases in the subsequent multilevel models.
friendship and kinship ties, organizational participation and neighborhood services, collective efficacy was still found to be a significant predictor of violence, suggesting that collective efficacy is conceptually distinct from these other concepts and maintains discriminant validity (Sampson, Raudenbush and Earls 1997).

This study is a seminal contribution to the literature on social disorganization theory for several reasons. The first reason is it is the foremost study to simultaneously test for the effects of structural social disorganization variables with mediating effects of social ties (i.e., private control), organizational participation (i.e., parochial control), neighborhood services (i.e., public control), and the novel concept of collective efficacy using multilevel modeling to adjust for measurement error due to clustering effects resulting from homogeneity across neighborhoods. The second reason is the use of a newly-developed “necometric” methodology to measure neighborhood level characteristics by aggregating individual-level survey data to the neighborhood level to measure social control and social cohesion concepts, which facilitated this first empirical test the utility of the concept of collective efficacy (Raudenbush and Sampson 1999:3).

Sampson’s (2012) highly-influential book entitled *Great American City: Chicago and the Enduring Neighborhood Effect* is a landmark study of social disorganization and neighborhood crime. It focuses on the effects of collective efficacy on a multitude of outcomes in Chicago neighborhoods over more than two decades. Specifically, Sampson’s (2012) book thoroughly investigates the longitudinal dimensions of social disorganization, specifically by using empirical data from the PHDCN and diverse secondary data sources to show how neighborhoods maintain similar levels of crime, racial/ethnic composition and concentrated disadvantage over time despite population
changes. Furthermore, he argues that racial segregation and the geographic concentration of poverty have profound influences on neighborhood-level processes, including legal cynicism, perceptions of law enforcement and disorder, and collective efficacy, all of which are also perpetuated over time despite population turnover in neighborhoods.

Applying complex social network and geospatial analysis methodologies, Sampson (2012) finds that informal social control and social cohesion processes, among other social phenomena, operate within intra and extra-neighborhood network relationships which transcend the physical neighborhood. Thus, these findings lead to the conclusion that current conceptions of neighborhoods as physically bounded are limited and problematic. Overall, Sampson (2012) concludes that: 1) high levels of collective efficacy are stable in neighborhoods over time and predict not only lower crime rates, but also obesity rates, health outcomes, teenage pregnancy rates, community involvement, immigration patterns, altruism and the strength and density of leadership networks, 2) that neighborhood effects are persistent over time and are not due to selection biases caused by individual-level characteristics of individuals choosing to move to each neighborhood, and 3) that neighborhoods and their contextual effects will remain relevant in the future despite critics’ calls for the decline in their importance due to increasing interconnection due to communication technology and greater migration of residents within and across states in the U.S.

This section reviewed the development and theoretical background of social disorganization theory. The next section provides a review of the recent empirical support in the literature for social disorganization theory. This is followed by a discussion of the
historical development and main concepts of institutional anomie theory and a review of empirical tests of institutional anomie theory.

b. Social Disorganization Theory Literature Review

Social disorganization has received substantial empirical support across numerous recent studies with diverse samples of neighborhoods, cross-national research designs and both cross-sectional and longitudinal samples (e.g., see Kubrin and Weitzer 2003 for a review; see Pratt and Cullen 2005 for a meta-analysis; Osgood and Chambers 2000; Lee and Martinez 2002; Nielsen, Lee and Martinez 2005; Steenbeek and Hipp 2011; Bruinsma et al. 2013). Several of these recent studies have examined new and unique directions in research on social disorganization theory that are especially pertinent to this dissertation. The areas of research in these studies include the effects of immigrant composition on neighborhood crime rates (Nielsen, Lee and Martinez 2005), the extension of social disorganization theory to rural areas (Osgood and Chambers 2000) and the application of geospatial analysis methods to test for crime clustering (Lee and Martinez 2002; Bruinsma et al. 2013). Other key issues examined include controversy over the correct operationalization of a “neighborhood” (Hipp 2007), the theoretical integration of social disorganization and routine activity perspectives (Smith, Frazee and Davison 2000), and finally, the longitudinal (instead of cross-sectional) effects of social disorganization on neighborhood disorder and crime rates over time (Steenbeek and Hipp 2011).

First, an important recent direction in social disorganization research is the inverse effect of immigrant concentration on crime rates, which was discovered while extending the geographical scope of the theory and testing various structural
contingencies. For example, Nielsen, Lee and Martinez (2005) investigated the effects of social disorganization measures on the outcomes of motive-specific (i.e., expressive and instrumental) counts of homicides disaggregated by race and ethnicity. They used data from 196 Census tracts in San Diego, California and 70 Census tracts in Miami, Florida. The explanatory variables included place and ethnic-specific economic disadvantage measures, a neighborhood instability index and a recent immigration measure (percentage of residents who immigrated recently between 1980 and 1990). Using negative binomial regression models, equality of regression coefficient tests between both locations and correcting for spatial autocorrelation, the authors found that economic disadvantage and residential instability were positively associated with expressive homicides and negatively associated with the percentage of recent immigrants in most models but the results were different for black and Latino homicides.

For the instrumental homicide models, disadvantage was positively associated with robbery homicide for blacks in both cities but not for Latinos, while residential instability was not significant and the percentage of recent immigrants was negatively associated with robbery homicide for blacks. Moreover, for drug-related homicides, disadvantage was positively related to black homicides in both cities but not for Latinos, while residential instability was positively related to Latino homicides in San Diego and recent immigration was negatively associated with black homicides in Miami and positively associated with black homicides in San Diego. Overall, this study provides considerable support for the immigrant revitalization perspective that recent immigration enhances social capital and informal social control which in turn reduces community crime rates. It also shows that social disorganization predictors apply differently
dependent on the crime motive, geographic location and racial/ethnic context (Nielsen et al. 2005).

Second, Osgood and Chambers (2000) sought to extend the scope of structural social disorganization predictors beyond urban areas. They utilized data from 264 nonmetropolitan areas (i.e., counties) in four states (Florida, Georgia, South Carolina and Nebraska) with measures of social disorganization including residential instability, ethnic heterogeneity, family disruption, low economic status, population density and proximity to urban areas on the outcome of juvenile violence arrest rates. Using negative binomial regression models, the authors concluded that residential instability, ethnic heterogeneity and family disruption were associated with juvenile violence, supporting the application of social disorganization theory outside of urban areas. The authors conclude by calling for more research with larger samples of counties across more states with hierarchical linear modeling techniques and note that “themes from social disorganization theory have a broader application to communities of all sizes” (Osgood and Chambers 2000:108). This important conclusion is relevant for this dissertation, as I hypothesize that social control and social cohesion processes will be present at both the county and neighborhood-level.

Third, two important studies using geospatial analyses techniques are by Lee and Martinez (2002) and Bruinsma et al. (2013). Lee and Martinez (2002) investigated the key element of social disorganization theory that racial/ethnic heterogeneity and recent immigration increase crime rates. They analyzed gradated maps of homicide rates, recent immigration and black poverty and point pattern maps of Haitian and African American homicides in 12 Census tracts in North Miami between 1985 and 1995. They found that
the immigrant revitalization perspective was supported by showing a negative relationship between recent immigration and crime, while the positive effect of the concentrated disadvantage element of social disorganization was replicated.

Bruinsma et al. (2013) tested six different models of social disorganization with data from 3,575 individuals within 86 neighborhoods in The Hague, The Netherlands. Ecological measures of traditional structural social disorganization measures, family disruption, local friendship networks, organizational participation, unsupervised peer groups, neighborhood trust and collective efficacy were assessed for the outcomes of overall crime rates and offender rates (i.e., the number of suspects living in each neighborhood). Contrary to previous tests of social disorganization, the authors found that social capital, friendship networks, organizational participation and unsupervised peer groups did not predict offender rates, while only low socioeconomic status and family disruption were significant correlates of offender rates. For crime rate outcomes, the authors found similarly conflicting findings, with significant results in the direction expected by social disorganization theory for only ethnic heterogeneity, single-parent families, organizational participation and local friendship networks. Bruinsma et al. (2013) conclude that their test of social disorganization in a different cultural context suggests that the perspective is not necessarily a general theory cross-nationally as is argued, and that additional tests should be conducted with the same (or similar) measures used in U.S. studies of the theory in diverse cultural contexts.

Fourth, Hipp (2007) outlined a novel approach to the study of social disorganization in neighborhoods by using neighborhood crime and disorder to demonstrate how social processes operate at different levels of analysis and aggregation.
To test for the effects of structural social disorganization measures on perceptions of disorder and crime at different levels of aggregation, he utilized longitudinal data from three time periods with 25,332 household time points from the U.S. Census American Community Survey with respondents nested within Census blocks and tracts. Overall, Hipp (2007) found that population heterogeneity significantly predicted perceptions of crime and disorder for all levels of aggregation, economic resources showed stronger support at the block-level, and single-parent families had block-level effects on perceived disorder but tract-level effects on perceived crime. Taken together, these findings suggest that the level of aggregation has important effects for the significance and magnitude of effects, and this should be taken into account in research on neighborhood effects. This potential issue is addressed in this dissertation, in that it uses Census tracts as one of the two units of analysis.

Fifth, Smith, Frazee and Davison (2000) simultaneously tested elements of both social disorganization theory and routine activities theory. They used data from 12,081 face blocks in a midsized southeastern U.S. city with measures of traditional social disorganization variables (i.e., population heterogeneity, economic disadvantage and residential instability), land use measures of suitable targets and guardianship, and interaction terms of social disorganization measures and land use measures with the outcome of robbery rates. The authors found significant interaction effects between percentage of single-parent households and concentration of hospitality providers and nightlife venues/alcohol outlets (e.g., bars, restaurants and gas stations), and between the distance from the central business district and residences, vacant lots and nightlife venues/alcohol outlets. These findings show that measures of family disruption from
social disorganization theory, and motivated offenders and suitable targets from routine activities theory are jointly supported, providing empirical evidence for the utility of an integrated theoretical model of both theories at the neighborhood-level.

Sixth, Steenbeek and Hipp (2011) examined social disorganization theory with longitudinal instead of cross-sectional data (i.e., the approach in almost every other test of the theory). They tested how social cohesion and social control predict future crime and disorder, and conversely, how crime and disorder predict future social cohesion and social control. Analyzing panel data from The Netherlands on 37,637 residents nested within 74 neighborhoods from six time periods with cross-lagged full information maximum likelihood estimation methods, they found that while cross-sectional analyses were similar to previous tests of social disorganization, their longitudinal analyses showed that disorder affects future levels of actual and potential for social control, and residential instability, which then in turn further enhanced levels of disorder in the future. These findings show that cross-sectional analyses of social disorganization may be limited and that future tests should use longitudinal approaches when possible.

c. **Institutional Anomie Theory**

The institutional anomie theory of crime was recently developed by Messner and Rosenfeld (2001; originally published in 1994) and emerged from the broader literature on micro and macro-level strain theories based originally on the seminal article by Merton (1938). Since the fundamental elements of institutional anomie theory are drawn from and based on Merton’s (1938) classical strain theory, I first review this theory and its empirical support. In his article, Merton (1938) critiques American society as a social structure that places a strong emphasis on the institutionalized goal of economic (i.e., material) success yet does not supply the legitimate means (e.g., financial resources) for
many individuals in society to actually achieve this success goal. From this basic premise of a goals-means gap, Merton (1938) develops an analytic typology in which he lays out five potential adaptations\(^8\) to this social and cultural arrangement in the United States. The five adaptations Merton (1938) identifies and describes are conformity, innovation, ritualism, retreatism and rebellion.

Of these five adaptations to American society, the two that are most important to this dissertation and that provided the intellectual inspiration for institutional anomie theory are conformity and innovation. Merton (1938) argues that the majority of Americans generally favor the adaptation of conformity when possible, in which they use the legitimate means (e.g., higher education, a stable career and a modest or high income) to attempt to achieve the institutionalized goals of economic and material success. Yet, millions of Americans do not have the legitimate means to achieve the institutionalized goal of economic success due to many factors. These include, but not limited to, an economically disadvantaged family of origin, a lack of secondary/post-secondary educational achievement, a lack of human capital and saleable skills in the labor market, low levels of social capital which can block potential job opportunities, a criminal record and racism/geographic segregation due to being of a minority class and/or low socioeconomic status (Merton 1938; Granovetter 1973; Pager 2003; Seltzer et al. 2009; Krymkowski and Mintz 2011).

According to Merton’s (1938) strain theory, when individuals and groups pursue the institutionalized goals of economic/material success but do not possess the

\(^8\) For both Merton’s (1938) classical strain theory and Messer and Rosenfeld’s (2001) institutional anomie theory, the adaptations to a goals-means gap and criminogenic strain occur at the individual level. Also, in both theories, the collective anomie experienced in areas containing groups of residents with larger goals-means gaps and criminogenic strain occurs at the macro (i.e., structural) level.
institutionalized means to achieve this success, they feel strain (i.e., a breakdown of norms governing behavior). This strain can manifest as psychological stress and strain, and can cause the adaptation of innovation. Thus, Merton (1938) identifies the adaptation of innovation as causing crime, which occurs when individuals and groups\(^9\) use illegitimate means (i.e., crime and delinquency) to pursue the institutionalized goal of economic success by committing property and violent crime to obtain cash or items readily convertible to cash. Finally, Merton’s (1938) theory is not only limited to crime committed for economic ends, as the persistent strain caused by an inability to achieve institutionalized success goals can also manifest as frustration and anger. These can increase the probability of crimes such as expressive assault and homicide (e.g., aggravated physical battery, sexual assault and homicide due to arguments and anger).

Research on Merton’s (1938) anomie theory has received mixed support and only a few key studies have operationalized and empirically tested specific elements of the theory. First, Figueira-McDonough (1983) used data from high school students on academic performance and educational aspirational goals to test the effects of a gap between legitimate means and institutionalized goals on delinquency. The study used a sample of 1,735 tenth graders from nine Midwestern high schools with subcultural (i.e., adolescent-normative/nuisance crimes), property and violent delinquency outcomes, an item measuring how much the participants valued school as “imparting skills relevant to

\(^9\) Although Merton’s (1938) classical anomie theory was originally intended to operate on the individual-level, Baumer (2007) elaborated the theory in a multilevel framework, positing that both structural factors and the micro-level institutionalized goals vs. legitimate means gap affect individual-level criminal behavior. Moreover, Hughes, Antonacco and Botchkovar (2017) empirically tested this multilevel elaboration of the theory using data from the one city in the Ukraine and one city in Russia with instrumental crime outcomes. They found mixed support for the theory, with evidence for the effects of financial dissatisfaction on crime, as well as significant effects of neighborhood anomie but no evidence for the significant moderation effects of one’s level of commitment to monetary success goals.
future life” (to measure commitment to institutionalized success goals), and academic performance items (to measure commitment to legitimate means) (Figueira-McDonough 1983:266). Using ANOVA models and cross-tabulations to test Merton’s adaptations of rebellion, retreatism, utilitarian (innovation) and ritualism, Figueira-McDonough (1983) found that students in the rebellious and retreatist groups were more likely to engage in self-destructive delinquency, and the utilitarian group was more likely to engage in property-related delinquency. Thus, Merton’s (1938) theory was partially supported. Yet, the methodological approach was rudimentary due to the time period in which this paper was published.

Second, Menard (1995) argued that previous tests of classical anomie theory were inadequate, oversimplified and ignored social-psychological and structural elements of the theory. Using data on 1,725 adolescents from waves 1 through 5 of the National Youth Survey (NYS), Menard (1995) created a measure of commitment to institutionalized goals by asking whether respondents thought it was important to obtain a good career after graduation, measures of commitment to illegitimate means by asking how wrong it was to commit delinquency, and lastly, a measure of anomie by constructing an index of six items measuring normlessness across different life domains. With path modeling, OLS and logistic regression models, Menard (1995) found that taking into account the goals-means gap and level of anomie (i.e., normlessness) improved upon past studies of strain theory. While other studies only explained 1 to 7% of variance, Menard (1995) explained up to 23% of the variance in delinquency, 14% in more serious offending and 34% in rates of marijuana use. He concludes that the “goals-opportunities discrepancy is relevant at the macrosocial, aggregate, societal level, not the
individual level according to Merton’s anomie theory,“ which suggests that the structural theoretical extension in the institutional anomie theory is more suitable to test the overall effect of anomie in society (Menard 1995:169).

Third, Chamlin and Sanders (2013) tested the joint effects of measures of acceptance of material success goals and absolute and relative deprivation on drug trafficking rates across 43 nation-states. This approach interprets classical anomie theory as a macro-level theory that is best applied to profit-motivated (i.e., instrumental) crime. To measure acceptance of material success goals, the authors use the percentage of respondents who think that less emphasis on money and material possessions is a bad thing, absolute deprivation was measured as the infant mortality rate, and relative deprivation was measured as the Gini index of household income inequality. Using OLS regression models and interaction terms between absolute deprivation and relative deprivation, and the measure of commitment to economic success goals, Chamlin and Sanders (2013) found that the interactions were significant for the outcome of drug trafficking. The authors conclude that this empirically supported test of Merton’s anomie theory demonstrates how cultural and structural dimensions of society jointly predict instrumental crime, and they call for more research on anomie theories with more refined indicators for concepts from anomie theory across diverse samples.

Drawing heavily from the intellectual tradition of Merton’s (1938) theory of anomie and strain, Messner and Rosenfeld’s (2001) institutional anomie theory sought to expand the scope of the theory by introducing the role of noneconomic institutions in causing crime. Specifically, they initially sought to explain why the United States has one of the highest rates of violent crime and homicide among industrialized, developed
nations. Later revisions and elaborations of the theory expanded its scope to other types of crimes (Bjerregaard and Cochran 2008; Messner, Thome and Rosenfeld 2008) and smaller units of analysis such as counties (Maume and Lee 2003). Much like Merton’s (1938) strain theory, the institutional anomie theory of crime also argues that crime results from a disjuncture between institutionalized economic/material success goals and the ability to achieve these goals with legitimate means. However, instead of focusing on the micro-level among individuals and small groups, the macro-level institutional anomie theory of crime argues that the United States is a society characterized by a strong pursuit of economic success goals over commitment to noneconomic institutions such as the community, family, education system, polity and religious institutions.

Yet, many residents living in the United States do not have the legitimate means (i.e., access to resources to allow upward mobility, higher education, human and social capital) to achieve these economic success goals (Messner and Rosenfeld 2001; DiPrete 2002). As such, when groups of people within larger geographic aggregates are unable to achieve these institutionalized goals with legitimate means, they begin to feel strain or “anomie,” which can increase the probability of committing crime resulting from persistent feelings of relative/absolute deprivation (Merton 1938; Stiles, Liu and Kaplan 2000), status frustration (Cohen 1955; Schaefer 2016) and/or to obtain money or goods that are readily convertible to cash (i.e., instrumental crime) (Messner and Rosenfeld 2001). Thus, a major difference between Merton’s (1938) classical strain theory and the institutional anomie theory is that the former can operate on both the micro and macro levels, while the latter is operating only on the macro level. Another key difference from the classical strain theory and the key contribution of institutional anomie theory is that
the latter contends that strong noneconomic institutions can act to reduce the crime-generating effect of high levels of economic dominance (i.e., inequality) for four reasons. Specifically, a strong commitment to noneconomic institutions can mitigate strain, increase the availability of noneconomic opportunities for success, socialize residents with conformist norms and non-criminal morals, and bond potentially deviant individuals and groups to conformist institutions that provide informal and formal social control (Messner and Rosenfeld 2001; Messner, Thome and Rosenfeld 2008).

Furthermore, Messner and Rosenfeld (2001) critique Merton’s (1938) strong emphasis on increasing the availability of legitimate opportunities, arguing that this approach may actually intensify pressure to pursue economic ends for all. This could further exacerbate feelings of anomie among individuals without legitimate means to pursue these opportunities. Thus, Messner and Rosenfeld (2001) argue that when the economy is dominant over the noneconomic institutions of the family, community, polity, education system, religious institutions, and the social welfare system (i.e., an institutional imbalance as is the case in the U.S.), three specific conditions result in this anomic society. These consequences are the accommodation, penetration and devaluation of institutions (Messner and Rosenfeld 2001; Messner, Thome and Rosenfeld 2008:168).

First, accommodation occurs when the strength of commitment to noneconomic institutions is reduced in favor of commitment to economic institutions. For example, the millions of fathers fixated on achieving the American Dream of economic success leads them to work overtime and on weekends as part of the increasing trend of “workaholism” (Piotrowski and Vodanovich 2006:86-90) instead of spending time with family, participating in community improvement gatherings and being active in the political
process. Second, penetration occurs when the logic of the market economy and economic norms of maximizing efficiency, singular commitment to profit motives and dehumanization become present in other institutional domains. One example is the recent trend in post-secondary education towards for-profit colleges and universities that seek to maximize profit at the expense of student welfare, educational advancement and occupational achievement (Kirp 2003). Another pertinent example in U.S. society is the rise in religious organizations such as new age religions and megachurches that seek to maximize profit and market dominance instead of cultivating spirituality among members (Moore 1994; Carney 2012). Third, devaluation occurs when noneconomic institutions and the roles enmeshed in them are lessened in importance, significance, status and value when compared to economic institutions and roles. Pertinent examples of this process include the lack of value and status placed on volunteer work in communities, schools and social welfare organizations (Sheptak and Menaker 2016), and underappreciation of unpaid work in the family context such as child rearing, elder care and household chores (Dodson and Dickert 2004).

Overall, the adaptations of devaluation, accommodation and penetration of noneconomic institutions occur within ecological units (e.g., states, counties and cities) to an increasing degree and intensity as the dominance of the economy increases and the strength of commitment to noneconomic institutions is reduced within these areas. These three consequences of an institutional imbalance that prioritize the economy over all other noneconomic social institutions have four pathways through which crime is increased among individuals and aggregated groups within ecological units\(^\text{10}\) (Messner

\[^{10}\text{Although the original institutional anomie theory is a macro-level theory examining the institutional imbalance and crime rates in aggregate units, it has recently been extended to include micro-level elements}\]
and Rosenfeld 2001; Messner, Thome and Rosenfeld 2008). First, internalized moral controls instilled by social institutions which compel people to act in conformity with the institutionalized norms to be law abiding and the informal mores to obey the law are mitigated in importance and reduced in their ability to prevent deviant behavior. Previous research has found that strong commitment to and involvement in social institutions results in reduced criminality in individuals and groups (Hirschi 1969; Wong 2005). The internalized moral beliefs instilled by these institutions (e.g., through family and religion) can then reduce crime (Baier and Wright 2011; Halpern 2001). Thus, areas in which the commitment to these institutions are weak are expected to have reduced internalized moral controls among residents and in turn higher crime rates (Messner, Thome and Rosenfeld 2008).

Second, levels of social cohesion are reduced at the macro-level. This is because the capitalist ideology of individualism, personal monetary success goals above all other goals and the marginalization of individuals and groups from positions of status and power in areas with a highly dominant economy are opposed to the concept of social cohesion (Denny 2001). Because high levels of social cohesion improve the cooperation, wellbeing and collective mobilization of all members of a society (Denny 2001; Chan, To and Chan 2006; Klein 2013), its low levels in a market economy result in pursuing economic success “by any means necessary” (including crime) with little regard for the
physical and/or economic wellbeing of other members of society (Messner and Rosenfeld 2001:8).

Third, informal social control is unable to be developed, cultivated and exercised among individuals and groups because the greater emphasis placed on pursuing economic success over commitment to noneconomic institutions diverts attention and time away from developing strong families, communities and education systems. All of these effectively reduce social control in neighborhoods, cities and counties. Since social control has been shown to reduce crime at the micro and mezzo levels through social bonds providing involvement, commitment, attachment and belief mechanisms (Hirschi 1969; Jenkins 1997; Wong 2005) and macro-level through informal social control processes (Sampson 1986), with less commitment to noneconomic institutions, these processes are reduced in importance and strength (Messner and Rosenfeld 2001; Messner, Thome and Rosenfeld 2008). Thus, the result is an increase in crime rates in aggregate areas with low social control.

Finally, the extent to which social networks provided by noneconomic social institutions can provide social support to individuals and groups is lessened in frequency and strength. This results in less exposure to emotional, esteem, informational, network and tangible social support (House 1981). This lack of or low level of social support has been shown to increase psychological strain, anger and anti-social behavior such as property and violent crime (Colvin, Cullen and Vander Ven 2002; Meadows 2007), and its mitigation would be greater in areas in which the commitment to noneconomic institutions is low and prioritization of the economy over all other institutions is high, resulting in higher crime rates.
These four consequences of reduced levels of internalized moral controls, social cohesion, social control and social support occur at multiple levels of analysis (i.e., in ecological units, among groups and at the individual-level). For the purposes of the development of the integrated anomic disorganization theory they occur at both the neighborhood and county-level when an institutional imbalance is present. Each of these four consequences and the concepts of social cohesion, social control and social support contained within them will be discussed in greater detail in this chapter in section 4 on the development of the integrated anomic disorganization theory.

**d. Institutional Anomie Theory Literature Review**

Since the institutional anomie theory has been developed more recently, few studies have partially tested its central hypotheses and conceptual linkages, demonstrating the need for further research. These studies include Chamlin and Cochran (1995), Messner and Rosenfeld (1997), Piquero and Piquero (1998), Salvolainen (2000), Maume and Lee (2003), Pratt and Godsey (2003), Kim and Pridemore (2005), Baumer and Gustafson (2007) and Bjerregaard and Cochran (2008). The literature supporting institutional anomie theory is reviewed in this section.

First, Chamlin and Cochran (1995) conducted the first empirical test of institutional anomie theory using data from all 50 states in the U.S. They used data on property crime and measures of economic and noneconomic institutions of religion, polity and family from 1980. The dominance of the economy was operationalized as the poverty rate, and interaction terms were used to test for the conditioning effects of the strength of noneconomic institutions on the criminogenic effects of the dominance of the economy. To operationalize the strength of noneconomic institutions, Chamlin and Cochran (1995) used secondary data on church membership among residents, percentage
voting in elections and the marriage to divorce ratio. While they found that the dominance of the economy did not have direct effects on property crime outcomes, the interaction effects between the poverty rate and each of the three measures of the strength of commitment to noneconomic institutions were significant. Overall, they found partial support for institutional anomie theory and called for additional research with more developed indicators for the key concepts and larger samples across different social contexts, both of which informed future work on institutional anomie theory.

Second, Messner and Rosenfeld (1997) moved beyond Chamlin and Cochran (1995), using a cross-national approach with modern industrialized nations as their unit of analysis. They tested the key arguments of institutional anomie theory with data on the dominance of the economy (the Gini coefficient of income inequality and an index of economic discrimination against social groups index) and the strength of commitment to the polity with homicide rates in 45 countries. To measure the strength of commitment to the polity, they constructed a decommodification index. This index measured the degree of social and material resources provided by the government, which could decrease citizens’ reliance on market forces and in turn create a more balanced institutional structure, resulting in reduced crime rates. They found support for the positive effects of economic inequality and negative effects of the decommodification index on homicide rates, with the United States having one of the lowest decommodification indices and one of the highest homicide rates. Thus, Messner and Rosenfeld (1997:1408) conclude that institutional anomie theory received moderate support and suggested that future researchers further “clarify the precise nature of the social mechanisms linking the
welfare state, the institutional balance and levels of crime and violence in market economies.”

Third, Piquero and Piquero (1998) conducted a partial test of institutional anomie theory by focusing on the dominance of the economy and the strength of commitment to the noneconomic institution of the education system. Using data from all 50 U.S. states and Washington, D.C., their main goal was to improve upon previous studies by conducting sensitivity testing with different operationalizations of the strength of commitment to three types of noneconomic institutions. Dominance of the economy was operationalized as the poverty rate, while the strength of the noneconomic institution of the family was measured as the percentage of single-parent families. They measured the strength of the polity as both the percentage of the population who voted in the 1988 presidential election and the percentage of state residents receiving any kind of government assistance or welfare benefits. The strength of the institution of education was measured as the percentage of residents currently enrolled in post-secondary education, the percentage of individuals who did not complete high school and the ratio of teacher annual salaries to those of other citizens (Piquero and Piquero 1998). The authors estimated OLS regression models with cross-product interaction terms between the poverty rate and the strength of noneconomic institutions of the family, polity and education system.

Piquero and Piquero (1998) found some support for institutional anomie theory. Specifically, they concluded that college enrollment moderates the direct relationship between the poverty rate and property crime. The strength of commitment to the education system and polity significantly conditioned the relationship between the
poverty rate and state-level violent crime rates. Sensitivity testing indicated that alternative operationalizations of the strength of the polity and education were not statistically significant. The authors recommend that future studies develop more precise, valid and reliable measures of the main concepts in institutional anomie theory. Overall, this study expanded the empirical scope of the theory to include both violent and property crime outcomes, and tested different operationalizations of the dominance of the economy and the strength of commitment to noneconomic institutions. This is a similar approach to the use of novel measures of the institutional imbalance used in this dissertation (Piquero and Piquero 1998).

Fourth, Savolainen (2000) utilized a similar approach to Messner and Rosenfeld (1997) by employing a cross-national perspective and research design, yet built on previous work by increasing their sample size to 81 nations (i.e., greater statistical power). They also tested for interaction effects between measures of economic inequality and welfare support provided by the government to citizens as the strength of the polity. Their main findings offer cross-national support for institutional anomie theory in that economic inequality was positively related to homicide rates, while high levels of social welfare spending interact with economic inequality such that its criminogenic effect is attenuated in magnitude. Overall, Savolainen (2000) concluded that the cross-national support strengthens the robustness of economic inequality as a predictor of macro-level crime and that welfare spending can provide marginalized populations with resources to reduce feelings of strain and anomie, thus buffering the criminogenic effect of the dominance of the economy on crime rates. Thus, this cross-national test provides partial support for institutional anomie theory in a non-US social context.
Fifth, Maume and Lee (2003) narrowed the focus of institutional anomie theory to the county level, with disaggregated homicide rates (i.e., instrumental, expressive and total) as their outcomes. They tested for both mediating and moderating effects of the strength of commitment to noneconomic institutions on the crime-generating effects of the dominance of the economy. The authors utilized data on county-level homicide rates (instead of property crime as was used in several previous studies), using data from the FBI’s Supplementary Homicide Reports to disaggregate total homicides in 454 urban counties into expressive and instrumental types. Maume and Lee (2003:1152) support the expansion of the scope of institutional anomie theory to counties as the unit of analysis, arguing that the “relationship between economic and noneconomic institutions specified by institutional anomie theory should hold across communities.”

Maume and Lee (2003) measured the strength of commitment to the polity as the average voting percentage in the 1988 and 1992 elections and the strength of commitment to the family as the divorce rate in 1990. They also measured the social institutions of religion, education and social welfare as the number of civically-engaged religious groups, the average educational expenditures per pupil, and the monthly welfare payments per person below the poverty line, respectively. Moreover, they operationalized the dominance of the economy as the Gini coefficient of household income inequality. Maume and Lee (2003) used negative binomial regression and interaction terms between the Gini coefficient and the five measures of the strength of noneconomic institutions to test the moderation hypotheses. Their results partially support institutional anomie theory and demonstrate that the Gini coefficient and divorce rate have significant direct effects on homicide rates (for both overall and disaggregated rates). The percentage of civically-
engaged religious adherents, of voting members of the population, as well as welfare expenditures per person, also had significant negative effects on homicide.

Maume and Lee (2003) found that the only measure that conditions the relationship between the Gini coefficient and all three types of homicide was welfare expenditures per person. As social welfare spending increases within a county, the criminogenic effect of the Gini coefficient on the rate of total, expressive and instrumental homicide decreases. For the test of the mediation hypothesis, they found that the effect size of the Gini coefficient was reduced by about 34% when controlling for all of the measures of noneconomic institutions. This study is the only one besides Baumer and Gustafson (2007) to apply institutional anomie theory to the county-level, an empirical approach which is applied and elaborated on in this dissertation.

Sixth, Pratt and Godsey (2003) conducted a cross-national study of social support (i.e., a measure of the strength of commitment to the polity), economic inequality and crime in a partial test of institutional anomie theory with the outcome of homicide rates. They found that economic inequality had positive effects on the homicide rate, while social support was negatively associated with homicide. They also found a significant interaction between economic inequality and social support, suggesting that high levels of social support can attenuate the criminogenic effects of a highly dominant economy. In concluding their discussion, Pratt and Godsey (2003:631) argue that future work should “clarify the core propositions of the theories tested [in the paper]—possibly with the intent of future integration” and conduct additional empirical studies of the emerging social support and institutional anomie theoretical frameworks.
Seventh, Kim and Pridemore (2005) tested the hypotheses of the institutional anomie theory that negative socio-economic change (i.e., a measure of the dominance of the economy) increases property crime and that the strength of commitment to noneconomic institutions conditions this relationship. They used data from 78 regions in Russia in the year 2000. Focusing on instrumental crime resulting from a highly dominant economy and weak non-economic institutions, their outcomes were the overall robbery rate and armed robbery rate. They measured socio-economic change as the change in population, poverty and unemployment between 1992 (right after the U.S.S.R. broke up) until 2000, and they added measures of the change in privatization and foreign investment to create an additive index. Furthermore, they measured the strength of family by reverse coding the proportion of single-parent households with at least one child, education as the rate per 1,000 people enrolled in college and polity as the percentage of residents registered to vote in the 2000 Russian presidential election. Using OLS models, they found non-significant results for their socio-economic change measure and the interaction of it with noneconomic institutions on robbery outcomes, and a significant negative relationship between the strength of commitment to the polity and the robbery outcome. They conclude that anomie theories that receive support in the United States and across nations may not generalize cross-culturally, but they caution researchers that the data obtained from the Russian context may not be valid and reliable due to government biases and reporting issues (Kim and Pridemore 2005).

Eighth, Baumer and Gustafson (2007) jointly tested Merton’s (1938) classical strain theory and Messner and Rosenfeld’s (2001) institutional anomie theory. Employing data from 77 geographic regions including counties and Metropolitan Statistical Areas in
the United States, they utilized measures of the use of legitimate means to achieve success and the level of commitment to institutionalized goals along with measures of the dominance of the economy and commitment to noneconomic institutions with the outcome of instrumental crime rates (burglaries, robberies, auto thefts and larceny thefts for each location in 1977). They constructed measures of the goals-means gap from aggregated individual-level data from two survey items from the General Social Survey, the Gini coefficient of household income inequality to measure the dominance of the economy, diverse sources to measure the strength of commitment to noneconomic institutions and crime rates from the Uniform Crime Reports. By aggregating individual survey responses, they examined how the gap between aspirations to achieve success and the availability of legitimate means interacts with the dominance of the economy and the strength of commitment to noneconomic institutions on instrumental crime outcomes (Baumer and Gustafson 2007).

Their independent variables included the dominance of the economy (measured as limited job availability, educational and economic attainment, and Gini coefficient of income inequality), and the commitment to noneconomic institutions of the family, education, polity, religion and community. Testing for both direct and moderating effects, instrumental crime rates are higher in ecological areas with larger disparities between aspirations to achieve monetary success and the availability of legitimate means (i.e., goals-means gap). Furthermore, they found that this positive relationship was conditioned (i.e., less pronounced) by the amount of welfare assistance and quantity of socializing with family. The criminogenic effects of a larger goals-means gap was also conditioned (i.e., more pronounced) for ecological units with high levels of inequality and low
economic and educational attainment. Baumer and Gustafson (2007) concluded that when commitment to social welfare and the family is stronger in a particular geographical area, the positive (i.e., criminogenic) effect of a larger aspirations-legitimate means gap on instrumental crime is reduced. In contrast, when a geographic area has high economic inequality, poor educational attainment and an underperforming labor market, the criminogenic effect of a larger aspirations-legitimate means gap on institutional crime is increased. As a call for future research inquiries, they emphasize the need to “reconsider linkages examined in our study with alternative measures, data sources and samples” (Baumer and Gustafson 2007:655), an approach which I employ in this dissertation.

Ninth, Bjerregaard and Cochran (2008) analyzed data from 49 nations on the economic dominance measures of the degree of economic freedom, social security spending and the Gini coefficient, and three measures of the strength of commitment to noneconomic institution measures. These variables include the family as an index of family disruption, education system as the pupil to teacher ratio and illiteracy rate, and the polity as 100 minus the percentage voting in the last election on the outcomes of the country-level homicide rate and theft rate. They found that the Gini coefficient was supported as a predictor of homicide rates, and that the strength of commitment to noneconomic institutions mediated and moderated the criminogenic effects of economic dominance on crime outcomes.

However, contrary to previous studies, Bjerregaard and Cochran (2008) found that greater social welfare spending was positively associated with the theft rate. Furthermore, the criminogenic effect of family disruption was amplified in countries with
higher levels of welfare spending. They reason that their findings show that support for institutional anomie theory is somewhat consistent across different units of analysis and crime types. However, they conclude that it is unclear whether the strength of commitment to noneconomic institutions moderate or mediate the effects of economic dominance on crime, calling for more research to examine this issue.

2. Synthesis of Theory and Literature

Synthesizing the theoretical frameworks of social disorganization theory and institutional anomie theory, and the empirical evidence for each theory presented in the previous sections, three conclusions can be reached. First, there is considerable overlap in the key concepts of social disorganization theory and institutional anomie theory, especially in the intervening concepts linking the structural measures with crime outcomes, including social cohesion, social control and social support. These conceptual similarities suggest that theoretical linkages can be made among these concepts, and they can be hypothesized to act as intervening mechanisms within the integrative approach. These linkages are defined and discussed in greater detail in the next section.

Second, recent studies empirically testing both theories independently tend to be moving towards integrating across theories and data sources, and they are expanding the theoretical scope. Social disorganization theory is being tested in different regions (e.g., in rural areas), while institutional anomie theory is being tested with larger samples of smaller ecological units (e.g., counties, metropolitan areas and states). This increasing trend suggests that more integration across theories, datasets, disciplines and methodologies should be conducted to further bring together these two macro-level frameworks. Third, from a methodological standpoint, the application of geospatial methods are becoming more prevalent in research on social disorganization theory while
the refinement of measurement is occurring more in research on institutional anomie theory. Thus, the current approach of testing social disorganization theory with innovative geospatial analysis techniques and the refinement of institutional anomie theory to the county and neighborhood-levels follows the recent trend. Furthermore, the integration is an important contribution to the literature which could motivate more research on both theories using geospatial analyses and on institutional anomie theory with smaller units of analyses, perhaps even extending its scope to the neighborhood-level.

3. Integrated Theories of Crime

In the past three decades, the scholarly literature on criminological theory has shifted increasing interest to integrated theories (Messner, Krohn and Liska 1989; Tittle 1995; Colvin, Cullen and Vander Ven 2002; Pratt and Godsey 2003; Tittle 2004; Wikström et al. 2012; Antonaccio et al. 2015; Rorie 2015). The approach of integrating theories of crime is defined as, “to combine, synthesize, or integrate one or more existing theories, or theory fragments, into more comprehensive or adequate formulations” (Tittle 1995:89). Current approaches to theoretical integration have recently led to the development of multilevel integrated theories including differential coercion-social support theory (Colvin, Cullen and Vander Ven 2002) and situational action theory (Wikström et al. 2012). According to Tittle (1995:115-122), there are four types of theoretical integration: structural, conceptual, assimilative and synthetic. First, structural integration occurs when the main components of existing theories are combined in sequences, when: 1) explanatory variables from one or more theories are used as dependent variables in other theories, or 2) by identifying conditions in which causal processes of a theory affects causal processes of one or more theories. Hirschi (1979)
calls this type of integrated theory “end-to-end” integration because it links theories and their respective variables in a logical causal sequence where outcome variables from one theory cause explanatory variables from another theory.

Second, conceptual integration occurs when a newly-identified or invented general causal process is applied to multiple theories. This occurs by 1) finding an abstract process that shows that multiple theories are conceptualizing the same underlying construct, or 2) merging two or more existing concepts from current theories into an overarching abstract concept or process. Hirschi (1979) deems this type of integrated theory “up-and-down” integration because it subsumes multiple theories into one or more unifying abstract processes to identify commonalities in the concepts of each theory. Third, assimilative integration occurs when a framework of abstract causal processes is developed to serve as a model to integrate further theories without consuming specific prior theories. In other words, this involves creating an abstract model that includes potential causal mechanisms that are present at all levels of analysis (i.e., micro, mezzo and macro) and elucidating how these are linked without identifying any specific a priori theory (Tittle 1995).

Fourth, synthetic integration consists of five elements. Tittle (1995:118) identifies synthetic integration as an “integration of integration methods...[which] combines the best features of extant modes in order to build a better integrated theory.” The components of synthetic integration include integrative abstraction, a central causal process, contingencies under which the theory operates differently, explicit articulation of the interlinkages between theories and their concepts, and finally, precision and depth in the definition and operationalization of concepts and causal sequences.
It is under the paradigm of structural (i.e., end-to-end) theoretical integration that I develop the anomic disorganization theory. Specifically, I use concepts from social disorganization theory and institutional anomie theory, explicate the causal processes that link the theories and concepts and discuss the contingencies under which they operate (e.g., conditioning effects of IAT variables on SD→crime relationships and in neighborhoods nested within counties). Moreover, I explain their interlinkages vis-à-vis the intervening concepts of social cohesion, social control and social support, and explicitly define and operationalize the key concepts with empirical data to provide the first test of the integrated theory. These specific processes will be explained and described in more detail in the next section and in Chapter 3: Research Methods.

4. Logical and Conceptual Development of Anomic Disorganization Theory

The integration in this dissertation is based on the synthesis of social disorganization theory and institutional anomie theory and the structural (i.e., end-to-end) integration approach discussed above as part of the ongoing trend in the criminological literature. Three major logical and conceptual linkages can be made to develop anomic disorganization theory. These three connections pertain to the major sociological and criminological organizing concepts of social cohesion, social control and social support. In this context—for the purposes of the development of anomic disorganization theory—all three concepts are defined by their most general definitions and are present at both the micro and macro level but principally the latter.

The primary theoretical and conceptual model visually displaying these relationships is shown in this chapter in Figure 1. First, the concept of social cohesion is defined as “the willingness of members of a society to cooperate with each other to survive and prosper” (Stanley 2003:5). Second, the concept of social control is defined as
“the capacity of a society to regulate itself according to desired principles and values” (Janowitz 1975:82). Third, the concept of social support is defined as individual and group feelings “of being cared for and loved…esteemed and valued…and [belonging] to a network of communication and mutual obligation” (Cobb 1976:300). These three concepts act as intervening mechanisms between institutional anomie and social disorganization concepts, and the outcome of neighborhood violent and property crime rates.

Concepts from the former theory include the dominance of the economy and the strength of noneconomic institutions, whereas concepts from the latter theory include measures of residential instability, economic disadvantage and racial/ethnic heterogeneity. I argue that a highly dominant economy and weak commitment to noneconomic institutions at the county-level reduce the intervening concepts of social cohesion, social control and social support within counties, which then amplifies the crime generating effects of social disorganization concepts in neighborhoods subsumed within such counties. Since these intervening (i.e., mediating) concepts have been operationalized in many ways across studies, the theoretical and conceptual model of the proposed integrated theory in Figure 1 does include each of the three abstract concepts yet does not suggest an indicator. Furthermore, the intervening concepts are not empirically tested in the theoretical model in this dissertation. The reasoning for this analysis approach is described in section 6a in the current chapter and is discussed in greater detail in Chapter 6: Discussion and Conclusion.
Since social disorganization theory operates within neighborhoods that are located within larger geographic areas (e.g., neighborhood clusters, cities, metropolitan statistical areas, counties, and states), researchers have found that the larger social context within areas can influence outcomes in neighborhoods and communities subsumed in them. Of particular relevance for this dissertation is how economic dominance and the strength and

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11 While stronger noneconomic institutions are generally hypothesized to reduce crime rates (i.e., an inverse relationship) as is shown in Figure 1, the coding of the divorce rate (indicator for family) and pupil-to-teacher ratio (indicator for education system) are interpreted as having hypothesized direct (i.e., positive) relationships with crime rates. These empirical relationships are discussed in greater detail in Chapter 4: Results from Conventional Statistical Analyses.

12 For example, Ramey (2013) investigated the immigrant revitalization perspective by testing the effects of immigrant composition of neighborhoods on violent crime rates using data from Census tracts in 84 established and new immigrant destination cities. He found that the city-level context of the type of immigrant destination affected the relationship between immigrant composition and crime, such that the protective effects of immigration on crime rates was greater in established destination cities.
commitment to noneconomic institutions, including the family, community, polity, education system, religious institutions and social welfare system, can influence levels of social cohesion, social control and social support within counties. While these concepts are usually applied to smaller geographic units including neighborhoods, studies have tested the effects of social cohesion, social control and social support on crime in larger ecological units (e.g., counties). Moreover, since the valid measurement of these three concepts relies on the aggregation of individual-level survey responses, they are argued to act as intervening mechanisms in the anomic disorganization theory model. However, they are not empirically quantifiable in this dissertation due to data limitations.

Previous studies have found considerable support for the crime mitigating effects of social cohesion, social control and social support on crime. Hirschfield and Bowers (1997) tested the effects of social cohesion on crime rates using data from Great Britain in 1991 in disadvantaged and advantaged neighborhoods. They found that disadvantaged areas with high levels of social cohesion have lower crime rates than disadvantaged neighborhoods with low levels of social cohesion. Guthrie (1994) investigated the effects of formal and informal social control on violent crime outcomes with a sample of 121 U.S. counties from the year 1986 and found support for crime-mitigating effects of measures of informal social control, including the percentage of high school dropouts and percentage of poverty among African Americans. Furthermore, Sampson (1986) tested the effects of formal and informal social control in cities on the outcomes of robbery.

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13 In this study, cities are very similar to counties in their size, heterogeneity and macro-level indicators, making the extension of the concept of macro-level social control to counties a logical and consistent approach.
and homicide in 1980 in 171 U.S. cities with populations of greater than 100,000, and he found that macro-level social control reduces robbery rates.

Social support has emerged as a major organizing concept in criminology (Cullen 1994; Antonaccio et al. 2015). Some studies have found a negative relationship between social support and crime using multiple units of analysis (e.g., Hannon and DeFronzo 1998; Colvin, Cullen and Vander Ven 2002; Worrall 2005). For example, Hannon and DeFronzo (1998) tested for the effects of social support on property and violent crime rates across 406 large metropolitan counties in the United States, finding significant negative effects on property crime rates. Worrall (2005) also investigated the relationship between social support and index crimes using data from all 58 California counties between 1990 and 1998 (522 total observations), finding very limited crime mitigating effects of social support.

The ways in which I argue that these three concepts operate in the anomic disorganization theory are as follows. When the economy is the dominant social structure in a county over noneconomic institutions, neighborhoods and the individual residents that comprise them are compelled to pursue economic ends by any means necessary (i.e., the most technically efficient means). Thus, they lack the social cohesion, social control and social support (and socialization) provided by strong noneconomic institutions to conform to social norms, exercise self-control and pursue conventional avenues for monetary success (Messner and Rosenfeld 2001; Messner, Thome and Rosenfeld 2008). Furthermore, the extent to which strain and anomie can manifest in individuals and groups is increased because less social cohesion, social control and social support resources are available to mitigate this strain and to provide greater access to legitimate
means to pursue conformist institutionalized goals, thus likely leading to higher crime rates.

This theoretical logic can be extended to social disorganization theory. Specifically, I argue that when neighborhoods with high levels of residential instability, economic disadvantage and racial/ethnic heterogeneity are located within counties with low social cohesion, social control and social support—which are the product of the institutional balance being tilted toward economic dominance—the criminogenic effects of these three variables should be more pronounced. This is because while high levels of social disorganization in neighborhood causes crime by lowering collective efficacy and social network ties among residents, these negative effects should be compounded and amplified even more in counties also characterized by low social cohesion, social control and social support due to their structural economic and noneconomic institutional characteristics.

In contrast, while low social cohesion, social control and social support caused by a county-level institutional balance tilted towards economic dominance can amplify the effects of social disorganization variables at the neighborhood level, the converse is also true. Specifically, in counties with the institutional balance tilted towards a strong commitment to the noneconomic institutions of the family, community, religious institutions, education system, polity and social welfare system should provide higher levels of social support, social control and social support. Neighborhoods subsumed in these counties should have reduced criminogenic effects of social disorganization on neighborhood-level crime outcomes. For example, if several neighborhoods have high levels of social disorganization but are located in a county with high-quality public
schools, involved community organizations, civically-engaged religious institutions and a generous social welfare safety net, then the criminogenic effects of social disorganization would be less pronounced. In contrast, if several neighborhoods that have high levels of social disorganization are located in a county with very high levels of economic inequality several negative consequences can occur. When residents of these communities pursue economic goals for monetary success and this city or county also has poor-quality public schools, little to no community engagement, discriminatory/insular religious institutions and no safety net for unemployed or disadvantaged residents, then the crime-generating effects of social disorganization in these neighborhoods would be more pronounced/amplified.

a. Integration Across Methodologies and Disciplines

Beyond the conceptual and logical linkages in the integrated anomic disorganization theory discussed above, this dissertation also integrates across methodological approaches and disciplines. To supplement the conventional statistical analyses and to further test the proposed integrated theory for robustness with an interdisciplinary approach, geospatial analysis methods are used in the ArcGIS geospatial analysis program. Specifically, I employ an interdisciplinary approach by plotting the county-level crime and institutional anomie measures of the dominance of the economy and strength of commitment to noneconomic institutions to county-level maps of the United States. Research indicates that an interdisciplinary approach can enhance scientific inquiry because it addresses increasingly complex scientific problems more comprehensively and brings together disciplines to synthesize new knowledge that may not have been created within disciplinary boundaries (Gunawardena, Weber and Agosto 2010).
Furthermore, I also plot the neighborhood-level variables of crime rates, residential instability, economic disadvantage and racial/ethnic heterogeneity on census-tract maps of the United States for three cities (Portland, Oregon, Chicago, Illinois and Los Angeles, California) with low, moderate and high levels of economic inequality. Next, I compare the clustering of crime and theoretically relevant variables in neighborhoods with Global and Local Moran’s I in counties and neighborhoods, and geographically weighted regression techniques in these three cities (explained in detail in Chapter 3). As such, I investigate how institutional anomie theory operates spatially at the county-level, and I examine how social disorganization theory and crime clustering functions differently in cities based on their level of structural economic inequality.

5. Research Questions and Hypotheses

The synthesis of the literature on social disorganization theory and institutional anomie theory, and the integrated theoretical framework of both theories inform the following research questions and hypotheses. Each of these research questions and hypotheses is empirically tested in this dissertation. First, each theory is tested individually with social disorganization theory at the neighborhood level with data from 9,593 neighborhoods and institutional anomie theory at the county-level with data from 3,142 counties. Next, both theories are tested jointly with multilevel models with social disorganization theory at the neighborhood-level in 9,365 neighborhoods and institutional anomie theory in 83 metropolitan counties in which these neighborhoods are located. Lastly, cross-level interaction effects are used to test the conditioning (i.e., moderating) effects of institutional anomie theory measures on the effects of social disorganization measures on neighborhood-level crime rates.
Research Questions and Hypotheses:

Research Question 1: What is the relationship between structural social disorganization measures and neighborhood crime rates?
Hypothesis 1: Neighborhoods with high levels of social disorganization will have higher crime rates (See Figure 2).

Figure 2: Path Model of Neighborhood Level Social Disorganization and Crime Rates

Research Question 2: What is the relationship between institutional anomie measures of the dominance of the economy and strength of commitment to noneconomic institutions on county-level crime rates?

Hypothesis 2: Counties in which the economy is more dominant than noneconomic institutions will have higher crime rates (See Figure 3).

Hypothesis 3: Counties with a stronger commitment to noneconomic institutions will have lower crime rates (See Figure 3).

Hypothesis 4: The county-level strength of commitment to the family, polity, community, religious organizations, education system and social welfare system will reduce (i.e., moderate) the positive relationship between the dominance of the economy and county-level crime rates (See Figure 3).
Research Question 3: How do structural social disorganization theory measures and institutional anomie theory measures interact to predict neighborhood crime rates?

Hypothesis 5: The county-level dominance of the economy and the strength of commitment to the family, polity, community, religious organizations, education system and social welfare system will moderate the positive relationship between neighborhood-level social disorganization and neighborhood crime rates (See Figure 1).

Hypothesis 5a: When the county-level dominance of the economy is high, and the strength of commitment to the family, polity, community, religious organizations, education system and social welfare system is low, the positive relationship between measures of neighborhood-level social disorganization and neighborhood crime rates will be amplified.

Hypothesis 5b: When the county-level dominance of the economy is low, and the strength of commitment to the family, polity, community, religious organizations, education system and social welfare system is high, the positive relationship between neighborhood-level measures of social disorganization and neighborhood crime rates will be reduced.
6. Contributions of Dissertation

This dissertation contributes to the literature in several ways. As detailed next, these contributions include theoretical, substantive and methodological elements. The items discussed show the important gaps filled in the literature by this dissertation and also demonstrate its broader applications to criminological research.

a. Theoretical and Substantive Contributions

As described at the end of chapter 1, the proposed anomic disorganization theory of crime contributes to the criminological literature in five specific ways. First, the integrated theory seeks to explain a greater proportion of the variation in neighborhood crime rates than existing theories independently. One of the main goals of criminological research is to develop theoretical frameworks that are empirically testable and refining these theoretical approaches to maximize the percentage of variation in crime explained (Messner, Liska and Krohn 1989; Wilcox, Land and Hunt 2002:50; ASC 2016). This same goal is pursued in micro-level and macro-level criminological research. In micro-level research on crime, this goal is pursued by combining social psychological predictors (e.g., self-control and strain) and contextual factors (e.g., social control, social support and neighborhood effects) to maximize explained variation in individual-level criminal propensity and involvement (Messner, Krohn and Liska 1989; Tittle 1995).

In contrast, for macro-level crime research, approaches have included combining several variables to measure the same concept (e.g., social disorganization) or integrating variables from the theories (Messner, Krohn and Liska 1989) at the same level of analysis (e.g., social disorganization and routine activities perspectives; see Smith, Frazee and Davison 2000; Rice and Smith 2002). However, very few studies have extended the
multilevel approach utilized in micro-level research to study macro-level crime rates or pursued the central goal of criminological research of maximizing explained variance. Furthermore, current individual perspectives or integrated macro-level approaches have only explained less than half of the variation in neighborhood crime, leaving more than half of the variation in crime unaccounted for by any single or integrated theory (Pratt and Cullen 2005). Therefore, one of the three main goals of this dissertation is to maximize the explained variation in crime to better understand and predict neighborhood crime rates by integrating and testing the two theoretical perspectives.

Second, this dissertation investigates the potential criminogenic effects of a dominant economy, as economic inequality continues to grow in the U.S. using various measures of inequality (Kwon 2016). Previous research has consistently found that social inequality is associated with negative social outcomes, including poor mental and physical health (Kawachi and Kennedy 1999), overall mortality rates (Lynch et al. 1998), greater teenage births rates and obesity rates (Wilkinson and Pickett 2009), low levels of social trust and social capital (Kennedy et al. 1998; Kawachi and Kennedy 1999), and more violent crimes committed with firearms (Kennedy et al. 1998). However, no past work has investigated the effects of seven different measures of social inequality on crime rates with data for all 3,142 counties in the United States or the effects of county-level inequality on crime in neighborhoods nested within counties. Therefore, this dissertation will show how these two processes operate and will inform the scholarly literature and policy makers on the magnitude of the relationship between economic inequality and crime in neighborhoods and counties.
Third, the theory applies to neighborhood-level property and violent crime outcomes and explains the specific processes that contribute to each type of crime. While a large body of previous work has investigated the neighborhood-level correlates of neighborhood-level property and violent crime, no studies have empirically tested how county-level\textsuperscript{14} predictors affect neighborhood-level crime rates, and no studies have done so with overall crime disaggregated into property and violent crime. Moreover, this study compares the relative magnitude of variables from social disorganization theory and institutional anomie theory on both crime outcomes, testing how proximate (i.e., neighborhood) and distal (i.e., county) structural factors affect community crime.

Fourth, the theory provides policy makers and law enforcement agencies with diverse avenues for targeted interventions at multiple levels of municipal government (i.e., in communities and in counties). Currently, crime prevention approaches have taken disparate directions from more targeted, local approaches with community-based policing (Alpert and Dunham 1997; Roh and Oliver 2005) to more macro-level approaches at the city level with hotspots policing in major metropolitan areas (Braga and Bond 2008). The findings in this dissertation can establish whether neighborhood-level or county-level mechanisms explain more variation in crime, what the strongest predictors of crime are, and lastly, how county-level predictors condition structural correlates of crime at the neighborhood-level. With these results, policy makers and law enforcement can best use

\textsuperscript{14}Importantly, Ramey (2013) investigated the effects of structural social disorganization and city-level measures using a multilevel modeling approach and data from the National Neighborhood Crime Study. The study found that the effects of social disorganization predictors varied based on the immigrant context of the particular city.
public funding to systematically develop intervention programs to target the most influential structural correlates of crime at the correct level of analysis.

Fifth, the theory hypothesizes about potential intervening mechanisms of social cohesion, social control and social support which link the two theories to inform future scholarly research. Although the proposed anomic disorganization theory is unable to test for the direct and mediating effects of these intervening concepts because of data limitations in the current datasets and their time period, future primary data collections could obtain individual-level survey data on social cohesion, social control and social support with respondents nested within neighborhood and counties. Taking on an econometric methodological approach (Raudenbush and Sampson 1999; Sampson 2012), these potential studies could aggregate these survey responses to the neighborhood and county levels to construct measures of these concepts. These constructed measures could then be assessed to determine how the county-level dominance of the economy and strength of commitment to noneconomic institutions affect the intervening concepts and how the intervening concepts moderate the relationship between social disorganization and crime.

b. Methodological Contributions

The proposed integrated theory makes five methodological contributions to the literature that are discussed in this section. First, the empirical testing of the theory partitions the percentage of the variance in neighborhood crime rates attributed to neighborhood-level and to county-level factors to determine which is more influential
and estimates random effects across units of analysis\(^{15}\). These features of multilevel modeling (Raudenbush and Bryk 2002) are particular useful as they show which structural factors at specific levels of analysis are most important in predicting the outcome of neighborhood crime. In addition, by using hierarchical modeling techniques that estimate regression coefficients with both fixed and random effects, this method can determine whether the correlates of neighborhood crime rates vary across counties (Luke 2004; Rabe-Hesketh and Skrondal 2012).

Second, the spatial component tests social disorganization theory in three cities with low, moderate and high levels of economic inequality (i.e., differential levels of economic dominance). Geospatial analysis methods including local indicators of spatial autocorrelation and geographically weighted regression are used to develop a typology of social disorganization theory in different city-level economic contexts. This methodological approach can determine whether correlates of property and violent crime have the same significance and magnitude in different contexts of structural social stratification. Additionally, it shows graphically how crime patterns and social disorganization are distributed and clustered based on the economic context of the larger ecological unit of the city, and this can potentially contribute to the development of different types of social disorganization theory based on the larger social context. For example, much like Ramey (2011) who found that the effects of immigrant composition on crime differed in two types of cities (i.e., established vs. new destinations), the present analysis of social disorganization variables in varying county-level contexts may reveal

\(^{15}\) The multilevel model generates estimates of the total variance explained collectively by the variables at each level of analysis. The random effects will be explained in more detail in Chapter 3 when discussing the Analytic Strategy.
that neighborhood-level variables operate differently contingent on the larger socioeconomic context. Thus, the results could contribute to developing multiple typologies of social disorganization theory taking into account the broader ecological context.

Third, the methodological approach shows how multilevel modeling techniques can be further extended to ecological research on crime and social phenomena in nested structures such as neighborhoods and counties, instead of only individual people nested within larger social contexts (or individual people over time; see Raudenbush and Bryk 2002). This approach is an interesting extension of the typical multilevel model to estimating the effects of macro-level variables within different ecological units which could be extended to study additional macro-level theories of crime. For example, routine activities theory (Cohen and Felson 1979) could be studied at the neighborhood level and coercion-social support theory could be simultaneously studied at the county-level to determine how variables from both theories jointly affect neighborhood crime rates.

Fourth, the study develops new measures for the institutional anomie concepts of the dominance of the economy and the strength of commitment to noneconomic institutions to guide future research on the theory. Studies that have empirically tested institutional anomie theory have predominantly used the Gini coefficient of household income inequality (Messner and Rosenfeld 1997; Baumer and Gustafson 2007) or measures such as the poverty rate (Chamlin and Cochran 1995), to operationalize economic dominance. The methodological approach in this dissertation adds six additional measures of economic dominance\(^\text{16}\) that have not been previously tested for

\(^{16}\) These measures are from the year 2000 and include Ricci-Schutz coefficient (also called Pietra’s measure) of income disparity, Atkinson’s measure of income disparity, Theil index of
crime outcomes. Moreover, the approach of measuring the strength of commitment to noneconomic institutions also goes beyond previous work. The strength of commitment to community is operationalized using a multidimensional index of social capital (Rupasingha and Goetz 2008) across all 3,142 counties in the U.S. In contrast, major tests of institutional anomie theory have only used rudimentary measures of the strength of commitment to community with small samples of geographic regions such as Baumer and Gustafson (2007:631) who used a four-item measure of the strength of community across “77 geographic areas in the United States for the mid-to-late 1970s.” These novel measures from a more recent historical period may provide stronger support for institutional anomie theory and could show that previous tests using the Gini coefficient or other measures of the strength of commitment to noneconomic institutions were limited in their utility.

Fifth, the general methodological approach in this dissertation exemplifies how macro-level researchers can integrate across disciplines and data sources to develop novel measures and methodological approaches to test existing theories independently and jointly. While integrated theories have flourished in the integration of micro and macro level perspectives (e.g., collective efficacy theory (Sampson 2012), situational action theory (Wikström et al. 2012) and coercion-social support theory (Colvin, Cullen and Vander Ven 2002), macro-macro integrations have been less prevent (e.g., Smith, Frazee and Davison 2000). Moreover, while some key studies have taken on an interdisciplinary perspective by utilizing geospatial analysis methods (e.g., Bruinsma et al. 2013; Erdogan, Yalcin and Ali 2013), the use of geographic information systems to more income disparity, Coefficient of variation for household income, Squared coefficient of variation for household income and the Entropy index of income disparity.
comprehensively test theories at the macro level (and micro level) is still in its early stages. Thus, future researchers can build upon the methodological approach in this dissertation to test individual and multiple criminological theories with methods drawn from the discipline of geography.

To summarize, in this chapter, I first reviewed the theoretical background of social disorganization and institutional anomie theory and discussed the most recent empirical findings supporting each theory. Second, I explained the major types of theoretical integration in criminology and described how I constructed the conceptual linkages in the integrated anomic disorganization theory within the structural integration approach. Third, I detailed the methodological and interdisciplinary integration in this dissertation and described the research questions and hypotheses that are empirically evaluated. Lastly, I posited the theoretical, substantive and methodological contributions to the literature made by the integrated anomic disorganization theory by examining its specific components. The next chapter describes the datasets used in the analyses, the measurement and operationalization of each concept, and the analytic strategies used to test each theory independently and within the integrated model.
Chapter 3: Research Methods

In this chapter, I first describe the nine secondary data sources that I use to operationalize measures of neighborhood-level crime rates and social disorganization concepts, and county-level crime rates and institutional anomie concepts. Second, I discuss the specific measurement and operationalization of each concept. Third, I detail the analytic strategies and rationales for the conventional and geospatial analyses to empirically test each theory independently and jointly in the multilevel model of anomic disorganization theory.

1. Data Sources

a. National Neighborhood Crime Study

The data source that is used to obtain neighborhood-level measures of social disorganization and crime is the National Neighborhood Crime Study (NNCS). This publicly-available dataset includes Census-tract level crime and socio-demographic data from 91 cities and 64 metropolitan areas, with 9,593 Census tracts in a representative sample of neighborhoods in large U.S. cities (see Figure 4 for map) from the years 1999, 2000 and 200117 (Peterson and Krivo 2000). This dataset is unique as it contains the largest collection of representative data on property, violent and overall crime from metropolitan neighborhoods in the U.S., obtained and aggregated from numerous police departments and law enforcement agencies. Moreover, these data were recently released (in 2010) to the public. The NNCS includes crime counts, rates and key structural

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17 Although these data are from the years 1999-2001, they are the most comprehensive extant neighborhood-level crime dataset that was available for United States metropolitan areas when conducting this study. Moreover, since both theories in this dissertation are argued to by general across places and across time (i.e., when using historical data), similar findings should result using more contemporary data (Shaw and McKay 1942; Messner and Rosenfeld 2001; Sampson 2012).
predictors from social disorganization theory at three aggregate levels of analysis: the
Census tract, city and metropolitan statistical area (MSA) (Peterson and Krivo 2000).

These data were collected based on a stratified random sample methodology
within each geographic region of the United States which had a resident population of at
least 100,000 in 1999. Crime data were aggregated from police department reports of
either Census-tract level crime counts or location-based crime reports of the seven FBI
Part I crimes of robbery, burglary, larceny theft, motor vehicle theft, aggravated assault,
homicide and rape (FBI 2015). In cases in which these data were not released by the
police department in a particular city or were not otherwise available, the “city was
replaced with an alternative place of similar size, racial/ethnic composition, and level of
poverty” (Peterson and Krivo 2000:1). In addition, data were excluded for Census tracts
with large institutionalized populations (more than 50%), very small numbers of
inhabitants (less than 300 residents), if the laws prohibited the release of specific address
data on violent crimes of rape and homicide, and if the validity of the police department
data could not be cross-checked against the Uniform Crime Reports for 1999-2001
(Peterson and Krivo 2000).

In the cities of Detroit, Houston, Milwaukee, Pittsburg and Seattle, offense counts
were drawn from Census tract boundaries from 1980 or 1990. In very few instances,
police departments did not have access to data for 1999, 2000 and 2001, and crime data
from 2002 were used instead. As a result, some missing data are present for the rape rate
and homicide rate (i.e., between 10% and 27.7% of census tracts) for 2000 and the three
years aggregated. In addition to the crime data, the NNCS includes measures of

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18 Although arson is also a Part I offense, it is not included in the NNCS due to its very infrequent
occurrence and inconsistent reporting standards for arsons for police departments.
theoretically relevant variables on items such as social disorganization, structural
disadvantage, socioeconomic indicators, labor market conditions, mortgage lending and
population characteristics extracted from eight additional publicly-available data sources,
including the U.S. Census at the Census tract, city and MSA level.

A key feature of these data is geographic indicators that allow for the Census-tract
measures to be linked to a specific U.S. county. However, despite this characteristic, no
studies have linked these data to county-level predictors to jointly test multiple macro-
level theories with a multilevel modeling approach. Instead, the NNCS has been used to
investigate diverse research topics. For example, the NNCS data have been analyzed to
test the relationship between immigrant concentration and crime in large metropolitan
areas of the United States using the immigrant revitalization perspective (Kubrin and
Ishizawa 2012; Ramey 2013; Lyons, Velez and Santoro 2013), the interaction effects
between neighborhood racial composition and city segregation on neighborhood crime
rates (Krivo, Peterson and Kuhl 2009; Peterson and Krivo 2009; Peterson and Krivo
2010), and the effects of financial investment in communities on crime rates (Saporu et
al. 2011). Moreover, more recent research using the NNCS data has examined land use
patterns and neighborhood violent crime using geospatial analyses (Browning et al.
2010), fringe banking (e.g., payday lending) and crime (Kubrin et al. 2011), and lastly,
the effects of city-level political context on the neighborhood population composition and
crime outcomes (Velez, Lyons and Santoro 2015).

b. Uniform Crime Reports

The data source that is used to measure county-level property and violent crime
rates is the Uniform Crime Reports (UCR) (FBI 2006). The Uniform Crime Reporting
program is conducted by the Federal Bureau of Investigation (FBI) under the direction of the United States Department of Justice. The Uniform Crime Reports are released publicly by the FBI every year and include (among other measures) county and state-level counts and rates of the eight Part I crimes of burglary, larceny-theft, motor vehicle theft, aggravated assault, forcible rape, homicide, robbery and arson. These data are aggregated from over 18,000 city, state, county, federal, college/university and tribal law enforcement agencies who submit data directly to the FBI or to state UCR program participants, who forward the data to the UCR program. In cases in which the data are not reported or are incomplete, imputation procedures are used at the local level and then data are aggregated to the county level.\(^{19}\)

Despite the limitations of the UCR, including potentially underestimating the total amount of actual crime as it relies on official reports (Grove, Hughes and Geerken 1985), data from the UCR have been used in numerous studies to investigate county and state-level crime patterns in the U.S. For example, several recent studies have investigated various criminological research questions using these data. The most recent of these is by Siegel et al. (2014), who investigated state-level firearm ownership and stranger/non-stranger homicide with data from between 1981 and 2010. Other notable investigations from the previous two decades include a study by Pyrooz (2012), which examined the relationship between structural conditions, and gang and non-gang homicide, in 88 large US cities between 2002 and 2006. Furthermore, Messner et al. (2005) also employed

\(^{19}\) See the National Archive of Criminal Justice Data (NACJD) website at http://www.icpsr.umich.edu/icpsrweb/content/nacjd/guides/ucr.html for more details about the Uniform Crime Reporting Program data collection procedures, imputation method for missing data and study design details.
UCR data to test the relationship between population changes and violence correlates on homicide outcomes across 68 U.S. cities between 1979 and 2001.

c. **ASU GeoDa Center for Geospatial Analysis and Computation**

The data source that is used to measure the degree of the dominance of the institution of the economy at the county-level is the Arizona State University GeoDa Center for Geospatial Analysis and Computation (AGCGAC 2016). This research center is a major source of spatial data on social, economic and political indicators aggregated from other datasets, including the U.S. Census. In addition, the ASU GeoDa Center is a leading institution for the development of geospatial analysis methodologies and publishes numerous macro-level studies of social phenomena at the neighborhood and county-level (AGCGAC 2016). For this dissertation, the particular data of interest include the economic indicators collected and publicly disseminated through the ASU GeoDa Center website. Specifically, this dissertation uses seven measures of income inequality\(^{20}\) at the county-level from the year 2000 to measure the dominance of the economy.

d. **US Census County and City Data Book**

The data source that is used to obtain county-level measures of the strength of commitment to the social welfare system is the U.S. Census (US Census 2016). Specifically, the U.S. Census County and City Data Book for the years 1999 to 2001\(^{21}\) is

\(^{20}\) The measures from the GeoDa Center used to operationalize the dominance of the economy are all from the year 2000 and include: the Gini Coefficient of Income Disparity, Ricci-Schutz coefficient (also called Pietra’s measure) of income disparity, Atkinson’s measure of income disparity, Theil index of income disparity, Coefficient of variation for household income, Squared coefficient of variation for household income and Entropy index of income disparity.

used to operationalize this concept (US Census 2001). The U.S. Census Bureau is the government entity that conducts decennial censuses of the United States population, and it also gathers data on a wide variety of social and economic indicators in surveys such as the American Community Survey, the Economic Census and the American Housing Survey.

Moreover, the U.S. Census Bureau provides many of its data products containing aggregated social and economic indicators at the county-level on publicly-available databases on its website. This feature is relevant for this dissertation because the County and City Data Book for 1999-2001 contains data from the same time period as the NNCS on relevant indicators of the strength of commitment to family, the education system and the social welfare system. Data from the U.S. Census County and City Data Books have been used in criminological studies to investigate county and city-level crime patterns in the U.S. For example, two more recent studies that use these data were Avakame (1998), who concluded that family stability reduced intimate homicides while female labor force participation increased intimate homicide victimization, and Martinez (1996), who found that economic inequality was associated with Latino homicide across 111 cities in 1980.

e. **Northeast Regional Center for Rural Development**

The data source that is used to measure the strength of commitment to the noneconomic institution of community at the county-level is the Northeast Regional Center for Rural Development located at the Pennsylvania State University (NRCRD 2016). This center is an organization that aggregates information on social and economic measures across geographic regions in the United States to provide researchers with data information on the specific methodology used to obtain these data and for a link to the details of the methodology of aggregating these data and their limitations.
to enhance regional prosperity and support sustainability within communities. Their mission statement describes their main goal as “providing research-based information that helps create regional prosperity through entrepreneurial and cluster-based innovation, while assuring balanced uses of natural resources in livable communities in the northeastern United States” (NRCRD 2016:1). By providing the general public and scholarly researchers access to their public database, they foster scientific inquiry into communities and their changing dynamics over time. The specific measure of the strength of commitment to community at the county-level is social capital in the year 1997 extracted from a publicly-available dataset on the website database (Rupasingha and Goetz 2008).

f. National Center for Family and Marriage Research

The data source that is used to measure the strength of commitment to the noneconomic institution of the family at the county-level is the National Center for Family and Marriage Research (NCFMR 2014). The NCFMR is a research center that is housed at Bowling Green State University and was established in 2007 with support from U.S. Federal Government agencies to conduct innovative and interdisciplinary research on families. According to their mission statement, the NCFMR’s central goal is “to improve our understanding of how family structure is linked to the health and well-being of children, adults, families, and communities and to inform policy development and programmatic responses” (NCFMR 2014:1). More specifically, the data source that is used to measure the strength of commitment to the noneconomic institution of the family is the divorce rate per 1,000 using county-level data on the adjusted divorce rate from all counties in the year 2000 (Glass and Levchak 2014).
g. **Center for Congressional and Presidential Studies**

The data source that is used to measure the strength of commitment to the noneconomic institution of the polity at the county-level is the Center for Congressional and Presidential Studies (CCPS 2016). The CCPS is a policy and academic research center located within the School of Public Affairs at American University in Washington, D.C. It was established in 1979 to bring “together public policy practitioners and academics to share their research, knowledge, and experiences in a series of advanced institutes, conferences, and workshops on applied politics” (CCPS 2016:1). Specifically, the data source used to measure the strength of commitment to the noneconomic institution of the polity is 2000 election data on voter turnout at the county-level for all U.S. counties collected and made publicly-available within the Federal Elections Project (Lublin and Voss 2001).

h. **Association of Religious Data Archives**

The data source that is utilized to measure the strength of commitment to the noneconomic institution of religion at the county-level is the Association of Religious Data Archives (ARDA 2001; ARDA 2016). The ARDA is a research organization founded in 1997 by the Department of Sociology at the Pennsylvania State University that conducts primary surveys of minor and major religious denominations and makes these data available to the public in online databases. The ARDA also obtains, aggregates, stores and disseminates local, national and international data on pertinent subject areas related to religion from other publicly-available sources such as the General Social Survey and Religious Congregations and Membership studies. These data focus on subjects including religious service attendance, religiosity, opinions on contentious
political issues among different religions, and religious participation (ARDA 2016). This
publicly-available database makes yearly reports available online in an effort to
democratize data access (ARDA 2016). For the year 2000, several data sources are
available, including detailed county-level data on religious adherence, which allows for
the operationalization of the concept of strength of commitment to religious
organizations. Specifically, I utilize the data collected by the Association of Statisticians
of American Religious Bodies published by the Glenmary Research Center and publicly
available online from the ARDA from 2000 on the percentage of religious adherents for
all 3,142 counties in the United States (ARDA 2001).

i. National Center for Education Statistics

The data source used to measure the strength of commitment to the noneconomic
institution of the education system is the National Center for Education Statistics (NECS
2016). This national organization aggregates, stores and disseminates data from state and
local agencies to conduct surveys of purposeful and stratified random samples of school
administrators, teachers and students. These aggregated survey data are publicly available
in their online databases to policy makers and academic researchers to support scientific
inquiry into educational topics (NCES 2016). Their purpose is to examine indicators of
educational success and progress in primary and secondary educational institutions in the
U.S. This dataset is relevant for this dissertation because it has historical data on variables
used to measure the strength of commitment to education. The publicly-available data I
use to measure the strength of commitment to education is from the 1999 to 2000 period
from the U.S. Schools and Staffing Survey and publicly available online from the NCES
(NCES 2001).
j. **Neighborhood-Level and County-Level Maps of the United States**

To supplement conventional statistical analyses, neighborhood-level and county-level maps of the United States are extracted from the ESRI geographic information systems database (ESRI 2016). First, for neighborhoods, these maps include shapefile template outlines of all Census-tracts in the three case study cities of Portland, Oregon, Chicago, Illinois, and Los Angeles, CA with low, moderate and high levels of economic inequality, respectively. They are used with ArcGIS v. 10.4 to plot data on crime and social disorganization from the NNCS to test how social disorganization theory operates differently with differential levels of economic inequality. Second, for counties, these maps include county-level shapefile template outlines of all of the counties in the United States in 2000. They are used with ArcGIS v. 10.1 to plot data on county-level violent and property crime rates, the dominance of the economy and the strength of commitment to noneconomic institutions for all counties in the U.S. (ESRI 2016). These maps are publicly available from the ESRI database, and contain the FIPS Census-tract and county code locators to allow them to be linked to Census-tract and county-level data from the other data sources.

2. **Measurement and Operationalization**

a. **Census Tract Crime Rates from NNCS**

The first dependent variables are neighborhood crime counts and rates which are extracted from the NNCS dataset\(^{22}\). Specifically, the three-year average property and

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\(^{22}\) Because the violent crime outcome variables are highly skewed, overdispersed and censored at 0, the effective equivalent of crime rates are analyzed using negative binomial regression with *crime counts* as the dependent variable and an exposure variable for population (Osgood 2000). The Census-tract population in 2000 is used as the exposure variable in the models predicting neighborhood crime, while the county population in 2000 is used as the exposure variable in the models predicting county-level crime.
violent crime counts in each Census tract for the years 1999-2001 are extracted from the NNCS database. The three-year averages minimize the effects of significant variation in the crime count from year to year for small units of analysis (Krivo, Peterson and Kuhl 2009). These measures were constructed in the NNCS dataset using the following procedure. The property crime measure is the total count of burglaries, larceny-thefts and motor vehicle thefts reported to police in the years 1999, 2000 and 2001 by Census tract, which is summed and then divided by 3 to construct the three-year average neighborhood-level property crime count. The violent crime measure is the total count of homicides, robberies, and aggravated assaults reported to police in the years 1999, 2000 and 2001 by Census tract, which is summed and divided by 3 to construct the three-year average neighborhood-level violent crime count. In addition, I constructed the three-year average Census-tract level property crime and violent crime rate by dividing the three-year average count measures by the Census-tract population in 2000, and multiplying each result by 100,000 for each Census tract. The negative binomial and multilevel regression models use the crime count outcomes, while the maps and geospatial analyses use the crime rate outcomes.

b. County-level Crime Rates from Uniform Crime Reports

The second dependent variable is county-level crime counts and rates which are extracted from the FBI’s Uniform Crime Reports dataset (FBI 2006). The three-year average property and violent crime counts and rates in each U.S. county for the years 1999-2001 are constructed from each year’s data on Part I crimes (i.e., 1999, 2000 and 2001) from the UCR database. Counties that were primarily covered by water (e.g., lakes), had under 100 in resident population and/or that were missing UCR data were
omitted from the analyses. If all three years were not available, then the remaining data from the available years was used instead. More specifically, the property crime measure is the total count of burglaries, larceny-thefts and motor vehicle thefts reported to police in the years 1999, 2000 and 2001 by county, which is summed and divided by 3 to construct the three-year average county-level property crime count that is comparable to the NNCS property crime measure. The violent crime measure is the total count of homicides, robberies and aggravated assaults reported to police in the years 1999, 2000 and 2001 by county, which is summed and divided by 3 to construct the three-year average county-level violent crime count that is comparable to the NNCS violent crime measure. I also constructed the three-year average county-level property and violent crime rates by dividing the three-year average crime counts by the county population in 2000 and multiplying this result by 100,000 for each county. The crime count outcomes are used in the conventional regression models, while the crime rate outcomes are used in the maps and geospatial analyses.

c. Census Tract Variables from Social Disorganization Theory

The first independent variables at the neighborhood-level are structural social disorganization measures extracted from the NNCS dataset. The same or very similar measures have been used in recent research on social disorganization and neighborhood crime (e.g., Sampson, Raudenbush and Earls 1997; Nielsen, Lee and Martinez 2005; Krivo, Peterson and Kuhl 2009; Ramey 2013). Specifically, measures from the NNCS dataset are used, including a residential instability index, a racial/ethnic heterogeneity index, and page 12 includes details of the concentrated disadvantage index.

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23 For more specific information regarding the methodology used to construct these three indices, see the NNCS codebook available at: http://www.icpsr.umich.edu/icpsrweb/RCMD/studies/27501Page 13 includes details of the residential instability index and racial/ethnic heterogeneity index, and page 12 includes details of the concentrated disadvantage index.
index, and a concentrated disadvantage index (Peterson and Krivo 2000). Each of the Cronbach’s alpha measures of internal consistency of the indices were already calculated in the NNCS dataset. First, a residential instability index for the year 2000 was constructed by summing the z-scores of the percentage of individuals five years or older who lived in a different home in 1995 and the z-scores for the percentage of occupied housing units that are renter occupied in each Census tract. This measure was then divided by two to yield the average. Higher values on this index indicate greater residential instability in Census-tracts. The alpha value for this index was \( \alpha = 0.69 \).

Second, a racial/ethnic heterogeneity index for the year 2000 was constructed by subtracting the summed squared values of the percentage of the population within each racial and ethnic group, and then subtracting this value from 1. The seven ethnic/racial groups included are “non-Hispanic Whites, non-Hispanic Blacks or African Americans, non-Hispanic American Indians and Alaska natives, non-Hispanic Asians, Native Hawaiians, or other Pacific Islanders, non-Hispanics of some Other Race or two or more races, and Hispanics or Latinos” (Peterson and Krivo 2000:13). Higher values on this index indicate greater racial and ethnic heterogeneity in the population in Census tracts.

Third, a concentrated disadvantage index for the year 2000 was created by summing the z-scores of four variables. These variables include the percentage of the secondary labor market sector in low-wage jobs, the percentage of the population between the ages of 16 and 64 who are not in the labor force or are unemployed, the percentage of female headed households and the percentage of residents whose income in 1999 was below the Federal poverty line. The measure was then divided by 4 to yield an
average. Higher values on this index indicate greater concentrated disadvantage in Census tracts. The alpha value of the index was $\alpha=0.91$.

**d. County-Level Variables from Institutional Anomie Theory**

The seven data sources described above are used to operationalize the concepts from institutional anomie theory including the dominance of the economy and the strength of commitment to noneconomic institutions at the county-level. In this section, I describe each measure in detail based on previous literature and explain its operationalization for the analyses in this dissertation. While these measures are limited due to the availability of publicly available data from the time period that is consistent with the crime data from the NNCS (1999-2001), measures that have been used in previous studies are grounded in the literature and have adequate face validity and internal consistency (Piquero and Piquero 1998; Maume and Lee 2003; Rupasingha, Goetz and Freshwater 2006:90; Baumer and Gustafson 2007).

*Dominance of the Economy*

To test and compare model specifications with different measures of the dominance of the economy, seven measures are used to measure this concept, only one (i.e., the Gini coefficient) of which has been used in previous tests of institutional anomie theory (Maume and Lee 2003; Baumer and Gustafson 2007). I will describe each measure and briefly explain its relevance for operationalizing the dominance of the economy drawing from the work by De Maio (2007) reviewing measures of social inequality used in empirical research. All seven measures are used to assess the dominance of the economy at the county-level for the year 2000. Each of these individual measures of the county-level dominance of the economy is tested in the bivariate
correlation analyses and multivariate analyses with county-level crime, and the Gini coefficient is used in the moderation models to be consistent with previous tests of institutional anomie theory.

First, the Gini Coefficient of income disparity is the most common measure of income inequality and varies between 0 and 1. For this measure, a value of 0 indicates perfect equality in which all individuals or households have an equal share of income, while a value of 1 indicates that one individual or household has all of the income or wealth and all other individuals or households have none. Higher values on the Gini coefficient indicate higher levels of economic dominance. By using this measure, I am replicating the operationalization approach in previous studies of institutional anomie theory (Baumer and Gustafson 2007; Maume and Lee 2003). This operationalization of economic dominance as the Gini coefficient is consistent with Messner and Rosenfeld’s (2001) theoretical argument that increasing inequality due to capitalism results in increasing anomie in geographic regions (e.g. counties). Moreover, a study by Chamlin and Sanders (2013) of 43 nations found that the Gini coefficient was moderately correlated ($r=.19$) with the extent to which residents felt like an emphasis on material possessions and money is a desirable life goal. Finally, research by Antonaccio and Tittle (2007:936) on the degree of capitalism and homicide across 100 countries suggests that the Gini coefficient is a valid measure of economic dominance, since “unequal distribution of wealth [is one of the] by-products of unrestrained capitalism.”

However, other measures may better capture economic inequality or dominance. Thus, second, the Ricci-Schutz coefficient (also called Pietra´s measure or the Robin Hood index) of income disparity (2000) is “the maximum vertical distance from the
Lorenz curve to the 45° line of equality. It is called the Robin Hood index because it can be interpreted as the proportion of income that has to be transferred from those above the mean to those below the mean in order to achieve an equal distribution” (De Maio 2007:851). Higher values on the Ricci-Schutz coefficient of income disparity indicate higher levels of economic dominance.

Third, the Atkinson’s measure of income disparity (2000) is similar to the Gini index of inequality but is more sensitive to the degree of inequality in different sectors of the income distribution. More specifically, it uses weighting for different parts of the income distribution with a sensitivity parameter, and it can be used to compute the “proportion of total income that would be required to achieve an equal level of social welfare as at present if incomes were perfectly distributed. For example, an Atkinson index value of 0.20 suggests that we could achieve the same level of social welfare with only 1−0.20=80% of income” (De Maio 2007:850). Like the Gini coefficient, a value of 0 also indicates total equality while a value of 1 indicates total inequality. Higher values on the Atkinson’s measure of income disparity indicate higher levels of economic dominance.

Fourth, the Theil index of income disparity (2000) is a measure derived from the discipline of information theory, and it is calculated as the entropy in the income distribution. Kawachi and Kennedy (1997) explain it as having a potential range from 0 to infinity, and in contrast to the other measures, higher values on the Theil index of income disparity actually indicate a more equal distribution of income (i.e., greater entropy). Thus, higher values on the Theil index of income disparity indicate a less dominant economy. Fifth, the coefficient of variation for household income (2000) is
constructed by dividing the standard deviation of the income distribution by its mean value. Since distributions with greater income equality have smaller standard deviations, lower values of the coefficient of variation are present in more equal societies (or ecological areas). The squared coefficient of variation for household income (2000) is also used by squaring the coefficient of variation for household income to test for potential curvilinear effects of income inequality. Both measures range from 0 to infinity and their interpretation is more difficult than the Gini coefficient because they rely on a normal or near-normal distribution of income since very low or very high values of income (e.g., billionaires) may drastically change the mean and standard deviation values. Higher values on the coefficient of variation and on the squared coefficient of variation of income disparity indicate higher levels of economic dominance.

Sixth, the Entropy index of income disparity (2000) is very similar to the Atkinson’s measure in that it is also adds a sensitivity parameter to the Gini coefficient to increase sensitivity to the inequalities at the wealthier end of the distribution. However, unlike Atkinson’s measure, the Entropy index of income disparity can vary between 0 (complete equality) to infinity. Higher values on the Entropy index of income disparity indicate higher levels of economic dominance.

Family

The strength of commitment to the noneconomic institution of the family at the county-level is operationalized using measures from the National Center for Research on Families for the year 2000. Specifically, I use the adjusted divorce rate per 1,000 population for the year 2000 for counties. Thus, the divorce rate is used as a strength of
commitment to family measure. Higher values on the measure indicate a weaker commitment to the noneconomic institution of the family.

Community

The strength of commitment to the noneconomic institution of community at the county-level is operationalized using a theoretically-relevant measure from the Northeast Regional Center for Rural Development from the year 1997. Specifically, I used the county-level social capital index calculated by Rupasingha and Goetz (2008) which is available to the public in an online database. As a measure of the strength of commitment to community, social capital is defined as “features of social organizations, such as networks, norms, and trust, which facilitate action and cooperation for mutual benefit” (Coleman 1988; Putnam 1995:35).

This measure was computed in the following way based on the article that outlined the construction of this index24 (Rupasingha, Goetz and Freshwater 2006). First, the authors aggregated data from five sources, including the U.S. Census Bureau, County Business Patterns, U.S.A. Counties on CD, National Center for Charitable Statistics and the Regional Economic Information System on measures of the density of membership in voluntary organizations, voting patterns, response rate to the Census Bureau’s decennial census, and the number of tax-exempt non-profit organizations. Second, the social capital index was then constructed by extracting the principal components from all four variables and “the first principal component is interpreted as the index of social capital” (Rupasingha, Goetz and Freshwater 2006:90). The measure was then standardized, and it

24 While I describe the fundamental components of the social capital index, see Rupasingha, Goetz and Freshwater (2006) for the theoretical background, empirical justification and statistical procedures conducted to construct the index.
is used as a *strength of commitment to community index*. Higher values on the index indicate a stronger commitment to the noneconomic institution of community.

**Polity**

The strength of commitment to the noneconomic institution of the polity at the county-level is operationalized using measures from the Center for Congressional and Presidential Studies collected as part of the Federal Elections Project for the year 2000 (Lublin and Voss 2001; CCPS 2016). Specifically, I use the county-level percentage voting participation, which is the percentage of residents who voted in the 2000 presidential election. Previous research such as by Baumer and Gustafson (2007) used a similar measure to operationalize the strength of commitment to the polity. Higher values indicate a stronger commitment to the noneconomic institution of the polity.

**Religious Institutions**

The strength of commitment to the noneconomic institution of religion at the county-level is operationalized using a measure from the Association of Religious Data Archives for the year 2000 (ARDA 2001). Specifically, I use a measure of the county-level adjusted percentage of religious adherents in 2000. Since participation in organized religion has been found to reduce crime participation by instilling morality and the social bonds of involvement and belief (Johnson et al. 2001), the use of a measure of religious adherence (instead of religious affiliation) is a valid indicator of the macro-level strength of commitment to religion. Several recent studies have utilized these data this religious adherence measure with macro-level outcomes, including county-level civic engagement (Porter 2010) and county-level child poverty rates (Ranjith and Rupasingha 2012). According to the ARDA (2016:2), religious adherents are “all members, including full
members, their children and the estimated number of other participants who are not considered members; for example, the “baptized,” “those not confirmed,” “those not eligible for Communion,” “those regularly attending services.” Higher values on this measure indicate a stronger commitment to the noneconomic institution of religion.

Education System

The strength of commitment to the noneconomic institution of the education system at the county-level is operationalized using a measure from the National Center for Education Statistics for the year 2000 (NCES 2001). Specifically, I extracted data from the online database on the pupils per teacher from 1999-2000. Similar measures have been used by Maume and Lee (2003) and Baumer and Gustafson (2007) in previous tests of institutional anomie theory. Higher values of the pupil to teacher ratio indicate a weaker commitment to the noneconomic institution of the education system.

Social Welfare System

The strength of commitment to the noneconomic institution of the social welfare system at the county-level is operationalized using measures from the U.S. Census County and City Data Book from the year 2000 (U.S. Census 2001). This measure is similar to those used by Worrall (2005), who investigated the relationship between welfare spending and crime rates. I created a measure of the rate of welfare payments per person by dividing the total expenditures for the Supplemental Security Income program

25 Those “regularly” attending services include individuals who may attend services once a week but who are not official members of the particular religious denomination.

26 For states that did not report the student to teacher ratio for that particular year, I used data from alternative years including data from 1998-1999 for Virginia, 2003-2004 for Massachusetts, and 2004-2005 for Tennessee.
by the county population for each U.S. county. Higher values this measure indicate a stronger commitment to the noneconomic institution of the social welfare system.

e. Census Tract Control Variables

To control for covariates of neighborhood crime that are consistently supported in the literature and if omitted from the analyses could lead to biased results, several control variables at the Census tract-level are included. First, since previous research on the age-crime curve has found that adolescent and young adult males commit the majority of crime (e.g., Sampson and Laub 2005; Schwartz et al. 2009), I control for the proportion of males aged 15 to 24 in each Census tract in 2000. Second, past studies have consistently found that rates of violent crime tend to be higher in the southern regions of the United States (Huff-Corzine, Corzine and Moore 1986), so I include a variable coded as 1 if the particular Census tract is located in the southern region of the U.S. and coded as 0 otherwise.

Third, many studies have linked population density to higher crime rates due to more opportunities for motivated offenders to encounter suitable targets (Cohen and Felson 1979). Thus, I include a measure of the total population per Census tract in 2000 as an offset variable. Fourth, since recent research has typically found that the immigrant composition of neighborhoods affects the crime rate based on the immigrant revitalization hypothesis such that a greater percentage of immigrants lessens crime rates27 (e.g., Nielsen, Lee and Martinez 2005; Kubrin and Ishizawa 2012; Ramey 2013), I control for the percentage of new immigrants in 2000.

27 This operationalization is consistent with studies testing the immigrant revitalization paradigm such as Ramey (2013), who operationalized the presence of new immigrants as the “Percent of the total population in each Census tract that is foreign-born and entered the United States in 1990 or later.” See page 14 of the NNCS codebook for more information.
f. County-Level Control Variables

To control for covariates of macro-level crime that are supported in the literature and could lead to biased results if omitted from the analyses, several control variables at the county-level are also included (Maume and Lee 2003; Pratt and Cullen 2005). These variables are similar to those at the neighborhood level, as many macro-level correlates of crime are shared between these two ecological units. In particular, I control for the percentage of residents between the ages of 18 and 24 years old, the percentage of the population that is black, the percentage of the population that is Hispanic or Latino and the unemployment rate, all from the year 2000. In addition, I include a dummy variable coded as 1 if the county is located in the Southern U.S. and 0 otherwise. The theoretical and empirical justifications for these control variables are the same as for the neighborhood-level control variables.

g. Geographic and Location-Specific Variables

In addition to the variables used in the conventional statistical analyses, I also use several additional variables for the geospatial analyses of social disorganization in three cities with differential levels of economic inequality. First, I rank the Gini coefficient of income inequality of all 93 cities in the NNCS to determine which cities have the lowest, moderate and highest level of economic dominance (i.e., inequality). This ranking shows the cities in the NNCS dataset with the minimum, median and maximum levels of economic inequality. Second, I identify Portland, Oregon, Chicago, Illinois, and Los Angeles, California as cities with low (below the 25th percentile), moderate (between the

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28 Since social disorganization has been generally tested in larger, more populous urban contexts (Kubrin and Weitzer, 2003), I limit the choice of three cities to only those with over 250,000 in population.
25th and 75th percentile) and high (above the 75th percentile) levels of economic inequality.

Third, based on these rankings the three selected cities (Portland, OR, Chicago, IL, and Los Angeles, CA) are then separated from the main NNCS dataset and the Census tracts within them are plotted to Census tract shapefiles from the ESRI database29. Fourth and finally, the Census-tract level property and violent crime measures, and social disorganization measures of residential instability, economic disadvantage and racial/ethnic heterogeneity are plotted on the map for each city and are analyzed to determine how social disorganization operates differently in cities with different levels of economic inequality. While an extensive amount of criminological research has examined the Chicago context (e.g., Sampson 2012; see a review in Kubrin and Weitzer 2003), fewer studies have tested theories in Los Angeles (e.g., social disorganization/collective efficacy in Burchfield and Silver 2013) and Portland. Therefore, while the models for Chicago will determine whether previous findings on social disorganization are replicated, the models for Los Angeles and Portland will provide further tests of the theory in diverse context with varying levels of economic inequality.

3. Analytic Strategy

a. Census Tract Model of Social Disorganization Theory

Before testing the multilevel model of anomic disorganization theory, I first test social disorganization theory and institutional anomie theory independently. To test

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29 In addition to the varying levels of economic inequality and sufficiently large metropolitan population, the three case study cities were also selected due to having complete data on the variables of interest and diverse racial and ethnic compositions.
social disorganization theory at the neighborhood-level across 9,593 neighborhoods, I estimate two negative binomial regression models for the property crime outcome. Next, I estimate two negative binomial regression models for the violent crime outcome. The first model in both cases includes only the social disorganization measures alone, while the second model adds the control variables.

Negative binomial regression is the preferred statistical technique for the property and violent crime count outcomes because these dependent variables are count variables and are overdispersed (i.e., a mean greater than the variance). In this case, OLS regression would yield biased and inefficient coefficient estimates, and potentially misleading results in tests of statistical significance (Long 1997; Osgood 2000). Negative binomial regression is an extension of the Poisson model (usually used for count data) that is used in cases in which overdispersion is present. A gamma parameter is added to the Poisson model to adjust for overdispersion. Furthermore, the outcome variable is a count variable censored at 0, as some locations reported 0 crimes, justifying the use of negative binomial regression over other estimation methods. Thus, to test social disorganization theory at the neighborhood-level, negative binomial regression models were estimated (Long 1997).

Negative binomial regression conforms similar assumptions as OLS regression. These include: that the error terms must be independent of each other, that the model must be linear in its predictors and that multicollinearity among explanatory variables must be minimal. In contrast to OLS regression, negative binomial regression does not conform to the homoscedasticity in the error variance assumption or the normality of the error term (Hilbe 2011). To ensure that the statistical assumptions for negative binomial
regression were not violated, the following analyses were conducted (Long 1997). First, the assumption that the data must be overdispersed count data censored at 0 was tested by plotting separate histograms for crime in Census tracts and counties, and comparing the variance and the mean in the descriptive statistics (Long 1997; Osgood 2000). These tests indicate that the crime data at both levels of analysis are overdispersed count data and the negative binomial regression is the most suitable technique. Second, I checked for multicollinearity using variance inflation factors for all explanatory variables used in models collectively. The results show that all variance inflation factors are below 4 and as such, multicollinearity should not introduce inefficiency into the regression estimates. Finally, since negative binomial regression has different measures of model fit and does not result in a single explained variance measure like an $R^2$ in OLS regression, I report both the McFadden’s pseudo-$R^2$, and the alpha ($\alpha$) dispersion parameter as well as its significance for each model (Long 1997).

b. County-Level Model of Institutional Anomie Theory

To test institutional anomie theory at the county-level across nearly all 3,142 U.S. counties, I first estimate two negative binomial regression models with county-level property crime as the outcome and two negative binomial regression models with violent crime as the outcome. For both outcomes, I first estimate one model with the Gini coefficient and all six measures of the strength of commitment to noneconomic institutions. Next, I add the control variables into the model for each crime outcome. To compare the six additional measures of economic dominance with the violent/property crime outcome\(^{30}\), I estimate models with each economic dominance measure alone and

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\(^{30}\)Although Messner and Rosenfeld (2001) initially intended for institutional anomie theory to focus on lethal violence, and its structural and cultural causes in American society, the theory is also used to explain
all six measures of the strength of commitment to noneconomic institutions. Finally, I compare the incident rate ratios and the McFadden’s $R^2$ values for each model to determine which economic dominance measure has the strongest effect and which has a total model that explains the most variance. The statistical reasoning for using the negative binomial regression models for counties is the same as for the neighborhood-level models.

*Moderation Analyses*

To test for the conditioning effects of the six measures of the strength of commitment to noneconomic institutions on the effects of the dominance of the economy on property and violent crime outcomes, I construct multiplicative interaction terms between the Gini coefficient and each of the six measures of the strength of noneconomic institutions. Each of the measures was first mean centered prior to constructing the interaction terms to reduce potential problems with multicollinearity and make the interpretation of the main and interaction effects more intuitive\(^{31}\) (Long 1997). To test whether each interaction term was statistically significant, six models with each interaction individually were estimated for the property crime outcome and six were estimated for the violent crime outcome. Each model included the particular interaction term, Gini coefficient, and all six measures of noneconomic institutions and control variables.

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31 Since the social capital index was already standardized, it was not mean centered prior to constructing the interaction term.
c. **Multilevel Models**

To empirically test the proposed anomic disorganization theory of macro-level crime, I use multilevel modeling analysis techniques developed by Raudenbush and Bryk (2002). This methodological approach allows for the simultaneous testing of variables from multiple levels of analysis with nested data structures, in this instance, testing for social disorganization measures at the neighborhood-level with institutional anomie at the county-level in counties in which these neighborhoods are located. Multilevel modeling is the preferred technique in this case because it controls for clustering of observations which can introduce bias and inefficiency into the regression estimates, it shows the statistical significance of each variable at both levels of analysis independently, and it also allows for the partitioning of variance to determine what percentage of the explained variance is attributed to neighborhood-level factors and county-level factors (Raudenbush and Bryk 2002; Luke 2004; Rabe-Hesketh and Skrondal 2012). In this dissertation, Census tracts (i.e., neighborhoods) are the level-1 unit which are nested within counties, which are the level-2 unit.

The assumptions underlying multilevel modeling are that the error terms are normally distributed in level-1 and level-2 models and that the population variances are homoscedastic. However, since multilevel modeling is used in cases in which independence of error terms of observations is violated in single-level linear models, it only requires no correlation among the error terms at level-2 and also no correlation between level-1 and level-2 residuals (Raudenbush and Bryk 2002). Moreover, the multilevel model requires that a statistically significant amount of variation is present to explain at both level-1 and level-2, and also that the dependent variable (i.e., crime) is
required to be tested at level-1 (i.e., lowest level of analysis). Finally, the multilevel modeling approach allows for the testing of interaction effects between level-1 and level-2 predictor variables within the mixed effects model (i.e., with fixed and random effects) using the slope-as-outcomes models. These cross-level interactions show how effects of level-1 predictors on the outcome variable change based on the magnitude of level-2 predictors (Luke 2004).

Multilevel modeling is used to test the moderation hypotheses with multiplicative cross-level interaction terms between the social disorganization measures, and the dominance of the economy and strength of commitment to noneconomic institutions measures. This approach empirically tests the conditioning effects of a dominant economy and weak commitment to noneconomic institutions at the county-level on the statistical significance and strength of the association between social disorganization variables and crime at the neighborhood level. Since the crime outcomes are overdispersed count variables censored at 0 for both samples, a technique for the analysis of limited dependent variables is applied by using the multilevel overdispersed Poisson model in HLM7 with full maximum likelihood estimation techniques.

While the ideal or comprehensive test of anomie disorganization theory would consist of an analysis of a population of all neighborhoods nested in all counties in the United States, this hypothetical study is not possible due to data limitations at the neighborhood level. Therefore, I use the best available alternative which is the 9,365 Census tracts nested within 83 metropolitan counties from the National Neighborhood Crime Study. This dataset is particularly suitable for these multilevel analyses, because its statistical properties consist of a balanced dataset with relatively homogenous and
moderate to large sample sizes for neighborhoods at level-2 (Raudenbush and Bryk 2002).

The steps in the multilevel analysis of anomic disorganization theory are as follows. First, I estimate two models for each of the two crime outcomes to test for the main effects of variables from Census-tract social disorganization measures and county-level institutional anomie measures. The first model for each outcome includes each of the measures from both levels of analysis alone, and the second model adds the control variables at the Census-tract level and county levels. Next, I estimate 21 models to test the cross-level interactions of each of the three social disorganization measures, with the Gini coefficient and each of the six measures of the strength of noneconomic institutions.

d. Testing of County-Level Spatial Autocorrelation with Moran’s I

While the conventional statistical analyses are utilized to test the main hypotheses, additional geospatial analyses are used to test the distribution and clustering of key variables. More specifically, spatial representations of county-level crime rates and institutional anomie variables of the dominance of the economy and strength of commitment to noneconomic instructions and geospatial analyses of their clustering with Global and Local Moran’s I techniques are used to test the spatial patterns across the U.S. In particular, I map the measure of the dominance of the economy, the six measures of the strength of commitment to noneconomic institutions, and property and violent crime outcomes for 3,142 counties from the ESRI database (ESRI 2016). In the resulting map, the spatial distribution of each variable across the U.S. shows which counties and clusters of counties have high levels of economic dominance, low levels of commitment to noneconomic institutions and finally, high rates of property and violent crime.
To formally test the significance and magnitude of clustering in each of these variables across the U.S., a Global Moran’s I is calculated. Global Moran’s I is similar to a Pearson correlation coefficient, in that values closer to +1.00 represent positive spatial autocorrelation and values closer to -1.00 represent negative spatial autocorrelation. A value of 1 indicates that the values of the variable of interest are perfectly correlated/clumped with each other in space, a value of 0 indicates that the variable is randomly distributed, and a value of -1 indicates that the variable is perfectly dispersed (Lee 2001). Applied to macro-level crime, Andresen (2011:395) explains the use of this geospatial technique: “it is common to use Moran’s I in crime analysis, finding positive spatial autocorrelation among spatial units: high crime areas are close to other crime areas and low crime areas are close to other low crime areas…Moran's I is a “global” statistic in the sense that it provides an average representation of the study area.”

After computing this measure for each variable and finding a statistically significant Global Moran’s I statistic, I then calculate the Local Moran’s I for each of the variables. Anselin32 (1995:95) elucidates the meaning of contiguous geographic units with a statistically significant Local Moran’s I as “local spatial clusters, sometimes referred to as hot spots…identified as those locations or sets of contiguous locations for which LISA is significant.” Therefore, a significant Local Moran’s I shows which specific counties and clusters of counties with high (low) levels of the variable of interest are surrounded by other counties with high (or low) levels of the study variable. For

32 Although many other local indicators of spatial autocorrelation exist such as Geary’s C, the Local Moran’s I is the most applied in criminology and the social sciences when assessing the local clustering of a macro-level variable, and was first described and mathematically proven in the paper referenced here by Anselin (1995).
example, counties in Southern California all have high crime rates when compared to the average of all counties, so they would have a statistically significant Local Moran’s I and be represented on the map as having High-High clustering because they are contiguous areas with similarly high levels of crime rates. Thus, the maps in this dissertation show the clustering of crime, economic dominance and the strength of commitment to noneconomic institutions across counties in the United States.

e. **Local Dynamics of Neighborhood Crime in Three Cities and Visualization**

To investigate how social disorganization theory operates differently across three cities (i.e., Portland, Oregon, Chicago, Illinois and Los Angeles, California) with low, moderate and high levels of economic dominance, respectively, I focus on the local level crime patterns in these cities. I first map the social disorganization variables and crime outcome variables from the NNCS at the Census level with gradient maps. Next, I analyze these three city models with Local Moran’s I clustering analysis and geographically weighted regression to systematically investigate how social disorganization theory operates differently in cities with low, moderate and high levels of economic inequality.

Geographically weighted regression is a newly developed technique that controls for similarities between contiguous units such as Census tracts by adding a weighted spatial parameter to the regression analyses (Andresen 2006). Recent studies of neighborhood crime have used geographically weighted regression techniques to more thoroughly examine spatial patterns. For example, Bunting et al. (2018) used such a

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33 See section 2g in Chapter 3 (pages 89-90) for a detailed description of why these cities were selected as those with low, moderate and high levels of economic inequality.
technique to investigate predictors of larceny and aggravated assault in Miami-Dade County, Florida, and Graif and Sampson (2009) used it to spatially model immigration rates and diversity as correlates of homicide in Chicago, Illinois.

These spatial analyses show how the independent variables and dependent variables of property and violent crime cluster similarly or differently while controlling for the similarity across geographic units with a spatial lag and/or spatial error term in the regression model. Moreover, this technique calculates different regression equalities and corresponding coefficients, standard errors and R-squared values for each Census tract, visually illustrating how space influences the effects of the explanatory variables on crime outcomes. Overall, the geographic analyses show patterns in the variables that are not always evident in the conventional, numerical statistical analyses, provide robustness to the overall findings and allow for the testing of social disorganization theory in three different larger structural contexts.

To summarize, in this chapter, I detailed the data sources and the specific operationalization approach used to measure each concept from both theories. I also explained the analytic strategy to test the theoretical hypotheses in this dissertation, including both conventional and geospatial analysis methods. The next chapter contains the results from the conventional statistical analyses, first testing social disorganization theory and institutional anomie independently and then testing the multilevel integrated anomic disorganization theory.
Chapter 4: Results from Conventional Statistical Analyses

In this chapter, I first report the descriptive statistics and bivariate correlations between variables. Second, I describe the distribution of the county-level dependent and independent variables based on the gradient maps. Third, I discuss the results from the one level regression models of social disorganization at the neighborhood level and then for institutional anomie at the county-level. Fourth, I explain the findings from the multilevel model of anomic disorganization theory with Census-tracts nested within counties including both direct effects of variables from each theory and cross-level interactions between neighborhood and county-level variables.

1. Descriptive Analyses

a. Descriptive Statistics and Bivariate Correlations

Table 1 shows the descriptive statistics including the means, standard deviations, minimums and maximums for all variables used in the analyses at the neighborhood and county levels. Seven features of this table are particularly important to discuss, three for social disorganization theory and four for institutional anomie theory. First, there is a substantial range in crime across Census tracts, ranging from a low of 0 incidents (per 100,000) to a high of 171,739.13 incidents (per 100,000) for property crime, and a low of 0 incidents (per 100,000) and a high of 25,633.8 incidents (per 100,000) for violent crime.

Second, property crime has substantially more variation than violent crime, with a standard deviation of 8,274.93 for the former and 1,410.32 for the latter. Moreover, violent crime is far more skewed and overdispersed, with many more Census tracts reporting 0 violent crime incidents (37 tracts) when compared to property crime incidents.
(2 tracts) between 1999 and 2001. Third, there is also a considerable range for each of the three structural social disorganization measures, with residential instability ranging from -2.213 to 2.742, economic disadvantage ranging from -1.607 to 4.359, and lastly, racial/ethnic heterogeneity ranging from 0 to .805.

Fourth, at the county level, there is also a substantial range in the crime rate across counties, ranging from lows of 0 for both crime types, to a high of 12,290.02 for property crime and 4,798.12 for violent crime. Fifth, it is interesting to note that 31 out of the total 3,142 counties report zero violent crimes occurring, while only 5 counties report zero property crimes occurring between 1999 and 2001. Sixth, the Gini coefficient—as well as the other economic inequality measures—exhibit considerable variation across counties with a mean of .434 and standard deviation of .038. Interestingly, when comparing histograms of the Gini coefficient and the six measures of noneconomic institutions to the normal curve, each of the variables is very close to a normal distribution. The other six measures of economic dominance also exhibit substantial variation. Seventh, the mean values of other independent variables measuring the strength of commitment to noneconomic institutions reveal some interesting values. The mean number of students per teacher is 14.94 and the mean voter turnout was 53.5 percent, while the mean number of divorces and religious adherents was 17.91 and 628.70 per 1,000 population, respectively.

Furthermore, Table 2 shows the bivariate correlation coefficients for all variables used in the analyses at the neighborhood level, while Table 3 shows the bivariate correlation coefficients used in the analyses at the county level. Two features of each table are important to address. First, for Table 2, each of the three structural social
disorganization measures are significant and positively correlated (except for the heterogeneity and violent crime relationship) with both the property and violent crime outcomes. The strength of the relationship varies from a low of $r = .071$ for population heterogeneity and property crime, to a high of $r = .560$ for economic disadvantage and violent crime. Second, the bivariate relationships between the percentage of males aged 15 to 24 and both crime outcomes are significant and positive, whereas the relationship between percentage of new immigrants is significant and negative for property crime, and significant and positive for violent crime.

In Table 3, the bivariate correlations for counties show that, as expected, the Gini coefficient is significantly and positively related to both property ($r = .154$) and violent crime ($r = .312$) outcomes. Very interestingly, each of the seven additional economic dominance measures are also significantly and positively related to both crime types, except for the unsquared and squared coefficient of variation for property crime outcomes. Moreover, the Gini coefficient and all seven economic dominance measures have a significant and negative relationship with the social capital index and the voter turnout measure, and a positive and significant relationship with the divorce rate (except for the squared coefficient of variation). For the measures of the strength of commitment to noneconomic institutions, the social capital index and voter turnout measures are negatively associated with both crime types, while the rate of religious adherence is negatively associated with the property crime measure only. Finally, the pupil to teacher ratio and divorce rate are both positively associated with both crime types, while (contrary to the hypothesized direction) the social welfare spending per person measure was *positively* associated with each crime outcome.
b. *Geographic Display of Variables on Maps of the United States*

The maps in Figures 5 and 6 show the spatial distribution of property and violent crime per 100,000 population (respectively) in continental U.S. counties in the total sample of counties. The maps in Figures 7, 8, 9, 10, 11, 12, and 13 display the geographic distribution of the structural county-level predictors from institutional anomie theory including the Gini coefficient of household income inequality in 2000, social capital index of community in 1997, the pupil-to-teacher ratio in 1999-2000, the divorce rate per 1,000 in 2000, the voter turnout in the 2000 presidential election, the social welfare spending per person in 1999-2000, and the rate of religious adherence per 1,000 in 2000, respectively.

These variable maps reveal six results that are important to note. First, both crime types (Figures 5 and 6) are higher in southern regions of the United States, with counties in Arizona, central and southern Florida, Washington, Oregon, eastern Georgia and eastern South Carolina having the highest property crime rates. For violent crime, there are less counties with elevated crime rates, including those in central and southern New Mexico, southern Florida, and eastern Georgia and South Carolina.

Second, the Gini index of inequality (Figure 7) is highest in south Florida (Miami-Dade and Palm Beach counties), south central California (Los Angeles County), Washington, DC, New York City, and south Texas. Furthermore, the Gini index follows a similar trend to crime, in that inequality tends to be higher in southern counties (except for much of rural areas) and lower in northern counties (except New York City). Third, in contrast with the Gini index, the social capital index of community (Figure 8) tends to be lower in southern counties, and higher in northern and eastern counties. The counties
with the highest levels of social capital cluster in the West to Midwest regions, while the counties with the lowest levels of social capital cluster in the South and Southwest regions.

Fourth, the pupil-to-teacher ratio (Figure 9) is highest in the West (especially in California), Midwest (especially in Ohio, Indiana and Michigan) and Southern (especially in Florida) regions. The divorce rate (Figure 10) is more homogenous than other measures of noneconomic institutions across the United States, with urban areas having higher rates on average than rural areas, and Douglas County, Nevada and Las Vegas, Nevada as outliers with substantially higher divorce rates. Fifth, voter turnout (Figure 11) tends to be higher in northern counties and lower in southwestern counties, whereas social welfare spending per person (Figure 12) is highest in California, near Seattle and in the New England region. Sixth and finally, religious adherence (Figure 13) displays a very similar spatial patterning when compared to social capital, in that West and Midwest areas have clusters of high levels of both variables. However, religious adherence is also very high in the South, Southeast and in Utah, revealing that this variable has distinctive patterning due to southern Baptists and Mormon religious denominations in these geographic regions.

2. Multivariate Analyses

a. Census Tract Model of Social Disorganization Theory

Table 4 shows the negative binomial regression estimates (with tract population offset) for the one-level models of social disorganization predictors on property and violent crime outcomes at the Census-tract level. This allows the assessment of hypothesis 1, which states that neighborhoods with higher level of structural social
disorganization predictors will have higher crime rates. Models 1 and 3 show the effects of the three structural social disorganization predictors on property and violent crime outcomes, respectively, while models 2 and 4 show the same effects controlling for the percentage of males aged 15 to 24, southern location, and the percentage of new immigrants.

These multivariate analyses have several statistically significant results that are important to note. First, the effects of residential instability (b=.299) and economic disadvantage (b=.136) on property crime are both statistically significant and positive, and these effects remain (and increase) when controlling for covariates. The effect of population heterogeneity was not significant for property crime in model 1 but becomes significant in model 2 with the control variables added. Second, the effects residential instability (b=.208), economic disadvantage (b=.794) and population heterogeneity (b=.155) on violent crime are all statistically significant and positive, and these results remain and increase in magnitude when controlling for covariates. Third, the effects of percentage of new immigrants is significant and negative for property crime in model 2 (b=-.021) and violent crime outcome in model 4 (b=-.008). Furthermore, neighborhoods in southern locations have higher property and violent crime, while the proportion of males significantly and negatively predicts violent crime. The violent crime model contains a larger percentage of variation explained with $R^2=.077$ vs. the property crime model with $R^2=.019$. Therefore, hypothesis 1 is supported, with stronger evidence for the effects of structural social disorganization predictors for violent crime when compared to property crime.
b. County-Level Model of Institutional Anomie Theory

Tables 5 and 6 show the negative binomial regression estimates (with county population offset) for the one-level models of institutional anomie theory predictors on county-level violent and property crime outcomes, respectively. This allows for the assessment of hypothesis 2, which states that counties with a more dominant economy will have higher crime rates. Hypothesis 3 is also tested, which states that counties with stronger commitments to noneconomic institutions will have lower crime rates. Additionally, these analyses allow for the comparison of the Gini coefficient and the six additional measures of economic dominance. Models 1 shows the effects of the Gini coefficient and the measures of the six noneconomic institutions only for violent (Table 5) and property (Table 6) crime outcomes, whereas model 2 in both tables adds control variables for the percentage of males aged 15 to 24, percentage black, percentage Hispanic/Latino, percentage unemployed, and southern location. Models 3, 4, 5, 6, 7, and 8 show the results for the six additional measures of economic dominance and the measures of the strength of commitment to the six noneconomic institutions for the violent crime (Table 5) and property crime (Table 6) outcomes.

These multivariate models have several statistically significant effects that are important to discuss. First, across model 1 in tables 5 and 6, the Gini coefficient has a significant and positive effect on violent and property crime with the noneconomic institution measures but without control variables. However, the effect size is larger for

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34 It is important to note that these results showing that the Gini coefficient is reduced in magnitude/rendered non-significant when controlling for the strength of commitment to noneconomic institutions are consistent with Maume and Lee’s (2003) partial test of institutional anomie theory with homicide outcomes. They argue that Messner and Rosenfeld’s (2001) institutional anomie theory supports these findings, since it contends that economic dominance should have a direct effect on crime outcomes, but that this effect should be fully or partially reduced in the context of controlling for measures of a strong commitment to noneconomic institutions.
the Gini coefficient on the violent crime outcome in model 1 (irr=269.886; \( p < .05 \)) in table 5, when compared with the effect size for the property crime outcome in model 1 (irr=6.334; \( p < .05 \)) in table 6, and a non-significant effect for the violent and property crime outcomes in model 2 with controls. Thus, these results provide partial support for hypothesis 2, which states that counties with a more dominant economy will have higher crime rates.

Second, the significant effects of the strength of commitment to noneconomic institutions are more consistent than those for the Gini coefficient. For the violent crime outcome in model 2 in table 5 with controls, the effects of the pupil-to-teacher ratio (higher values=lower education quality) and divorce rate (higher values=lesser commitment to family) are significant and positive as hypothesized. The effects of voter turnout (irr=.179) and rate of religious adherence (irr=.999) were negative and significant as hypothesized. However, the coefficient for the social capital index and the welfare expenditures per person were both positive and significant—contrary to what was hypothesized. Thus, these results provide mixed support for hypothesis 3, which states that counties with a stronger commitment to noneconomic institutions will have lower crime rates.

For the property crime outcome in model 2 in table 6, the effects of the pupil-to-teacher ratio (higher values=lower education quality), is significant and positive as hypothesized. In addition, the voter turnout and religious adherence measures are also significantly and negatively associated with property crime as hypothesized. However, the coefficient for the effects of social capital were positive and significant—contrary to what was hypothesized. Finally, the divorce rate was not a significant predictor.
Third, much like the bivariate correlations, the effects of the control variables were in the expected direction, with a higher percentage black, percentage unemployed and southern location all associated with higher rates of both crime outcomes. However, the proportion of males between 15 and 24 was negatively associated with violent crime and did not significantly predict property crime. Finally, the explained variation in model 2 is low, with 0.7% of the variation explained in the property crime model (Table 5) and 2.8% of the variation explained in the violent crime model (Table 6).

Fourth, comparing the Gini coefficient and six measures of the dominance of the economy show that important results are present prior to introducing control variables (available upon request), as well as after adding the control variables shown in table 5 for violent crime (models 3-8) and property crime (models 3-8). The results before adding the control variables show that four of the measures have significant and positive effects on violent crime as expected (i.e., the Gini coefficient, Ricci-Schutz Coefficient of Income Disparity, Atkinson’s Measure of Income Disparity, Theil Index of Income Disparity). The coefficient of variation and squared coefficient of variation did not significantly predict violent crime, while the Entropy index was a significant predictor but in the wrong direction. The Ricci-Schutz Coefficient of Income Disparity has the largest incident rate ratio with 2280.158, followed by the Gini coefficient with 969.126, Atkinson’s Measure of Income Disparity with 941.054, and lastly, the Theil Index of Income Disparity with 5.977. The explained variance (McFadden’s $R^2$) has a similar

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35 Since pseudo-$R^2$ calculations in negative binomial regression models may underestimate the explained variance (see Long 1997), see the bottom of tables 5 and 6 for additional model fit statistics.

36 The significant effects of the strength of commitment to noneconomic institutions also remained in most cases when testing each measure of economic dominance.
pattern with $R^2=.018$ for the Gini and Ricci-Schutz Coefficient models, $R^2=.17$ for the Atkinson’s Measure, and $R^2=.016$ for the Theil Index. For the property crime outcome, the Gini coefficient without controls, as well as the Ricci-Schutz Coefficient and Atkinson’s Measure of Income Disparity are positive and significant predictors. Moreover, the coefficient of variation, squared coefficient of variation and entropy index are significant but in the incorrect direction. However, after adding control variables including the proportion of males aged 15-24, percentage black, percentage Hispanic/Latino, percentage unemployed and southern location, the results changed for both violent (Models 3-8 in table 5) and property (Models 3-8 in table 6) crime outcomes. Specifically, for violent crime in models 3-8 in table 5, only the coefficient of variation and squared coefficient of variation remain significant, yet in the incorrect direction as hypothesized. Moreover, for property crime in models 3-8 in table 6, all of the significant effects of the economic dominance measures in the hypothesized direction discussed above without control variables were not replicated. Thus, these results suggest that the Gini Coefficient and Ricci-Schutz Coefficient are the best supported economic dominance measures for both violent and property crime outcomes.

Table 7 shows the moderation models used to test hypothesis 4, which states that the strength of noneconomic institutions will moderate the positive relationship between the Gini coefficient and crime rates. Based on all 12 negative binomial regression models (6 for property and 6 for violent crime) with multiplicative interaction terms between the Gini coefficient and each of the six measures of commitment to noneconomic institutions, seven models resulted in statistically significant interaction terms. These
significant models are presented in models 1-7 in Table 7, with models 1-3 for property crime and models 4-7 for violent crime.

First, for property crime, the positive and significant interaction terms for the Gini coefficient by social capital and Gini coefficient by divorce rate (models 1-2) suggest that high economic dominance may amplify the relationship between these variables and crime. Moreover, the negative and significant interaction between the Gini coefficient and social welfare spending (model 3) suggests that greater spending may lessen the criminogenic effect of high economic dominance on property crime. Turning to the violent crime outcome, models 4 and 5 show that the same positive interactions from the property crime outcome are replicated for the Gini coefficient and social capital interaction, and the Gini coefficient by divorce rate. Furthermore, the same negative interaction is replicated for the Gini coefficient by social welfare spending interaction (model 7). Finally, there is a positive and significant interaction effect between the Gini coefficient and voter turnout measure ($b=13.944$), as shown in model 6. While two of the moderation models for property crime (Gini X divorce rate and Gini X social welfare spending) and two of the moderation models for violent crime (Gini X divorce rate and Gini X social welfare spending) were in the hypothesized direction, the direction of the interactions for the Gini coefficient by social capital index were opposite as was predicted for both crime outcomes. The Gini coefficient by voter turnout interaction was also in the opposite direction as was predicted for the violent crime outcome. Thus, these significant results provide mixed support for hypothesis 4, showing that seven models had significant interaction effects between the economic dominance measure and measure of the strength of commitment to noneconomic institutions.


c. Multilevel Model of Anomic Disorganization Theory

Table 8 shows the multilevel overdispersed Poisson regression estimates (with tract population offset) for the two-level models of social disorganization predictors at the Census-tract level and institutional anomie theory predictors at the County level on violent and property crime outcomes at the Census-tract level. First, these models provide an additional test of social disorganization theory in hypothesis 1, which states that neighborhoods with higher levels of structural social disorganization predictors will have higher crime rates. Second, the multilevel models allow for the assessment of hypotheses 5, 5a and 5b, which state that: a) county-level economic dominance will moderate (i.e., amplify) the positive relationship between structural social disorganization predictors and neighborhood crime rates, and b) that the strength of commitment to noneconomic institutions will moderate (i.e., reduce) the positive relationship between structural social disorganization predictors and neighborhood crime rates.

Models 1 and 3 show the effects of social disorganization measures and control variables including the percentage of males aged 15 to 24, southern location and the percentage of new immigrants, for property and violent crime outcomes, respectively. Models 2 and 4 add in the effects of the Gini coefficient and the measures of the six noneconomic institutions on the same outcomes. Models 5-7 shows the significant cross-level interactions between the Gini coefficient and concentrated disadvantage index (model 5), the rate of religious adherence and residential instability index (model 6), and the social capital index and racial/ethnic heterogeneity index (model 7) for the violent crime outcome. Finally, Figures 14, 15 and 16 show plots of the predicted effects of the same significant cross-level interaction effects shown in the models.
These multilevel models have several statistically significant coefficients that are important to describe. First, the effects of the three structural social disorganization predictors are significant and positive as predicted in property and violent crime outcome models (models 1-4). The largest effect size for property crime was for racial/ethnic heterogeneity (err=1.417), while the largest effect size for violent crime was for concentrated disadvantage (err=1.919). Thus, hypothesis 1 received additional support, which states that neighborhoods with higher levels of social disorganization predictors will have higher crime rates. Second, across all models for both neighborhood-level crime outcomes, the Gini coefficient only has a significant and positive effect on property crime. However, the effect size is larger for the Gini coefficient in model 1 without controls (err=160.677), when compared with the effect size for model 2 with controls (err=73.022) but it still retains significance. Third, the significant effects of the strength of commitment to noneconomic institutions are far less consistent than those for the Gini coefficient. In particular, the only significant coefficients were for the student to teacher ratio and the rate of religious adherence for the property crime outcome in models 1 and 2. However, while the effect of the rate of religious adherence was negative (as hypothesized), the effect of the student to teacher ratio was negative—the opposite of what was hypothesized. Fourth, the effects of the control variables were mostly in the expected direction, with a higher percentage of new immigrants significantly associated with lower rates of both neighborhood-level crime outcomes. However, the proportion of males between 15 and 24 was negatively

37 It is important to note that this finding on the reduction in the magnitude and statistical significance of measures of economic inequality (e.g., the Gini coefficient) is widely noted by scholars of institutional anomie theory (Messner and Rosenfeld 1997; Maume and Lee 2003) and structural causes of violence more broadly (Blau and Blau 1982; Fajnzylber Lederman and Loayza 2002).
associated with both crime types, contrary to what was expected. Moreover, the only significant county-level control variable was a direct effect of the unemployment percentage on the property crime outcome in model 2.

Fifth, model graphs in Figures 14, 15 and 16 show cross-level interaction effects between social disorganization predictors and institutional anomie predictors on the outcome of tract-level violent crime. In each figure, the estimated effect of the specific social disorganization predictor on the violent crime rate is plotted for counties at -1 standard deviation (in blue with a solid line), the mean value for the variable (in red with a dashed line) and at +1 standard deviation (in green with a dotted line). Figure 14 graphically shows the significant interaction effect between the Gini coefficient and concentrated disadvantage on violent crime. The graph shows that as the Gini coefficient increases in a county, the magnitude of the relationship between concentrated disadvantage and violent crime is amplified for lower values of concentrated disadvantage (i.e., the slope becomes steeper/higher). The estimated effect sizes of concentrated disadvantage at different levels of the Gini coefficient are as follows: b=0.8987 (p < .05) for counties with -1 standard deviation below the mean value of the Gini coefficient, b=0.7585 (p < .05) for counties with the mean value of the Gini coefficient, and b=0.6182 (not statistically significant) counties with +1 standard deviation above the mean value of the Gini coefficient.

Figure 15 graphically shows the significant interaction effect between the rate of religious adherence and residential instability index on violent crime. The graph shows that as the rate of religious adherence increases in a county, the magnitude of the relationship between residential instability and violent crime is reduced (i.e., the slope
becomes less steep). The estimated effect sizes of the residential instability index at different levels of the religious adherence rate are as follows: $b=0.3134 \ (p < .05)$ for counties with -1 standard deviation below the mean value of the religious adherence rate, $b=0.2397 \ (p < .05)$ for counties with the mean value of the religious adherence rate, and $b=0.1661 \ (p < .05)$ counties with +1 standard deviation above the mean value of the religious adherence rate.

Figure 16 graphically shows the significant interaction effect between the social capital index and the racial/ethnic heterogeneity index on violent crime. The graph shows that as the social capital index increases in a county, the magnitude of the relationship between racial/ethnic heterogeneity and crime is diminished (i.e., the slope becomes less steep). Overall, these significant cross-level interactions from the multilevel analysis provide partial support for hypotheses 5, 5a and 5b for the proposed anomic disorganization theory. Thus, the results suggest that structural social disorganization predictors may indeed predict crime differently in different ecological contexts of economic dominance and the strength of commitment to noneconomic institutions.

In summary, in this chapter I first described the descriptive statistics, bivariate correlations, and spatial distribution for crime outcomes, as well as social disorganization predictors at the neighborhood level and institutional anomie theory predictors at the county level. Next, I discussed the multivariate analyses of both theories on property and violent crime outcomes. Lastly, I explained the results from the multilevel analyses of variables from both theories, including main effects for each theory independently and cross-level interaction effects from both theories simultaneously. In the next chapter, I describe the results from the geospatial analyses, including analyses of institutional
anomie theory at the county level and social disorganization theory at the neighborhood level in three cities with low, moderate and high levels of economic inequality.
Chapter 5: Results from Geospatial Analyses

In this chapter, I first expand on the conventional statistical analyses in the previous chapter with geospatial analyses of institutional anomie theory at the county level by investigating the clustering of crime rates and independent variables. Second, I test social disorganization theory in different contexts of economic dominance with local indicators of spatial autocorrelation and geographically weighted regression in three case study cities with low (Portland, Oregon), moderate (Chicago, Illinois) and high (Los Angeles, California) levels of economic inequality.

1. Testing of Institutional Anomie Theory at County-Level

   a. Testing of County-Level Spatial Autocorrelation with Moran’s I

   To test the clustering of property and violent crime, and the Gini coefficient across US Counties, I use a Local Moran’s I geospatial analysis approach. The results are shown in Figures 17, 18 and 19. These results have three important features to note. First, both property crime and violent crime (Figures 17 and 18) have statistically significant high-high clustering in the southeast, south, central and southern California. In contrast, there is low-low clustering (with sporadic high-low and low-high county clusters) across the Midwest and northwest bordering Canada. Two important exceptions are elevated property crime in the Pacific Northwest (especially in Portland and Seattle) and elevated violent crime in New Mexico and Texas near the U.S.-Mexico border region.

   Second, the high-high clustering with low-high and high-low clustering surrounding it follows the rural vs. urban divide, in that high-high clusters tend to be in urban areas with larger populations. Third, the clustering of the Gini coefficient of

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38 See section 2g in Chapter 3 (pages 89-90) for a detailed description of why these cities were selected as those with low, moderate and high levels of economic inequality.
household income (Figure 19) demonstrates high-high clustering all throughout the south and southwest US, as well as coastal areas in central and southern California. Conversely, the Gini coefficient has low-low clustering throughout the Midwest, the inland mid-Atlantic area, western Pennsylvania and Utah.

2. Testing of Social Disorganization Theory at Census Tract-Level

a. Localized Patterning of Neighborhood Crime in Three Cities

To provide a better understanding of the ways in which social disorganization theory operates in cities with different levels of economic inequality, I construct choropleth maps and conducted geospatial analyses of property and violent crime in Portland, Oregon (Figures 20a-f), Chicago, Illinois (Figures 21a-f), and Los Angeles, California (Figures 22a-f). I first describe the results on the spatial patterning (i.e., local Moran’s I) of property and violent crime in each of the three cities. Next, I discuss the geographically weighted regression (GWR) results from each city on the effects of social disorganization predictors. I illustrate the spatial patterning of one structural variable from social disorganization theory for each city—concentrated disadvantage in Portland, racial/ethnic heterogeneity in Chicago and residential instability in Los Angeles—and also discuss the findings for the other structural predictors in each city. These results empirically show how crime is distributed differently across cities of varying levels of economic inequality. They also illustrate how each of the three structural social disorganization predictors have varying magnitudes of effects and explained variance (i.e., spatial heterogeneity) both across different cities39 and across different spatial

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39 In their widely-cited article discussing future research directions on social disorganization theory, Kubrin and Weitzer (2003) call for more tests of the theory in more diverse social contexts.
locations within individual cities. The examination of spatial heterogeneity is emphasized by Graif and Sampson (2009), who “argue on substantive grounds that neighborhood characteristics vary in their effects across neighborhood space” and also use geospatial methods (i.e., GWR) to examine predictors of homicide in Chicago communities.40

The maps of Portland depicted in Figure 20 show the study area (Figure 20a) and the distribution of the property crime rate (Figure 20b) and violent crime rate (Figure 20c). They also show the local Moran’s I of the property crime rate (Figure 20d), the geographically weighted regression (GWR)41 coefficient for the concentrated disadvantage index (Figure 20e), and finally, the local R² values for each tract from the same GWR model (Figure 20f). These maps show the following. First, as expected, property crime rates are higher than violent crime rates on average overall across the tracts in Portland, following the trend of property crime being more prevalent in general in metropolitan areas (FBI 2015; Sampson 2012).

Second, the geospatial analysis of clustering (Figure 20d) shows that a similar high-high cluster of neighborhoods in the north and west-central areas of the city have higher rates property crime. Conversely, a neighborhood cluster in the southwestern area of the city has low-low clustering, as well as low-high clustering on the border area with the high-high neighborhood cluster. Third, the analysis of clustering also shows that property crime is more diffused throughout the whole city, while violent crime tends to

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40 Since violent crime is more prevalent in Chicago and Los Angeles, and social disorganization theory has predominantly been used to explain community violence (Kubrin and Weitzer 2003), this type of crime is examined in these two case study cities. However, to determine how social disorganization predictors affect property crime outcomes—which has received less scholarly attention within a social disorganization framework—the models for Portland examine property crime outcomes.

41 For this and subsequent geographically weighted regression analyses, only the three structural social disorganization predictors are included as explanatory variables in the model.
be more tightly clustered. Interestingly, the high-high crime clusters in the central area of the city are surrounded by low-high clusters, which represent areas of transition between areas of higher structural social disorganization and lower social disorganization.

The maps of Chicago in Figure 21 show the study area (Figure 21a), and the distribution of the property crime rate (Figure 21b) and the violent crime rate (Figure 21c). Moreover, it also depicts the local Moran’s I of the violent crime rate (Figure 21d), geographically weighted regression coefficient for the racial/ethnic heterogeneity index (Figure 21e), and finally, the local $R^2$ value for each tract from the same GWR model (Figure 21f). These maps suggest the following. First, both property and violent crime are higher in areas bordering the city center near the lake, while suburban areas further from the city center have lower rates of both crime types. However, violent crime also tends to cluster in neighborhoods located inland south of the city center and in neighborhoods northwest of the city.

Second, the cluster analyses indicate that violent crime tends to have high-high clustering south and northwest of the city center in economically disadvantaged areas. Moreover, violent crime exhibits low-low clustering in the northern and southwestern suburban areas. This suggests that violent crime hotspots appear in bordering areas to the city center, which act as zones of transition (Shaw and McKay 1942) between high income neighborhoods and low-income neighborhoods.

The maps of Los Angeles shown in Figure 22 show the study area (Figure 22a), and the distribution of the property crime rate (Figure 22b) and violent crime rate (Figure 22c). They also show the local Moran’s I of the violent crime rate (Figure 22d), geographically weighted regression coefficient for the residential instability index (Figure
22e), and lastly, the local $R^2$ value for each tract from the same GWR model (Figure 22f).

These maps have three important characteristics. First, the spatial distribution of both crime types shows that while violent crime is more prevalent in south central areas of the city, property crime is far more spread out throughout the city across low, moderate and high-income areas (excluding Malibu and Beverly Hills).

Second, the cluster analyses indicate that low-low clusters of both property and violent crime are present in higher income areas in northern and northeastern areas near the ocean. In contrast, there is high-high clustering in south central and southeastern neighborhood clusters, which are inland and contain more economically disadvantaged residents. Third, there are four outlier neighborhood clusters with very high violent crime rates (see Figure 22c), while surrounding neighborhoods also have moderately high crime rates which diminish as the distance from such violence hotspots increases.

3. Testing of Multilevel Anomic Disorganization Theory

a. Testing of ADT with Geographically Weighted Regression

Finally, to better understand how social disorganization theory operates in each of the three cities while also taking into account spatial heterogeneity, geographically weighted regression models are used with all social disorganization predictors on both violent and property crime outcomes. The results revealed the following results for Portland, Oregon (Figure 20e and f), Chicago, Illinois (Figure 21e and f), and Los Angeles, California (Figure 22e and f). First, for Portland, the effect of concentrated disadvantage on property crime is positive (i.e., criminogenic) across the city, but the magnitude of the beta coefficient ranges from 256 to 14,008. Furthermore, the local $R^2$ ranges from .17 to .38, showing that social disorganization theory exhibits spatial
heterogeneity and, in turn, receives varying empirical support depending on the spatial location. Additional GWR analyses of the effects of residential instability and racial/ethnic heterogeneity (available upon request) show that while these measures are significant predictors of property crime, the effect size varies across neighborhoods and they are not significant in some neighborhood clusters. Finally, the local $R^2$ is higher in western neighborhood clusters and lower in eastern clusters, suggesting that other causal factors such as drug abuse (e.g., methamphetamine or opiates) may be influencing crime beyond the variables used in the models in the dissertation.

Second, for Chicago, the effects of racial/ethnic heterogeneity also vary in magnitude across the city with most tracts showing criminogenic effects, while several tracts have negative (i.e., crime-mitigating) effects of population heterogeneity. The beta coefficient for the racial/ethnic heterogeneity index ranged from -5,437 to 12,268, while the amount of explained variation (i.e., $R^2$) ranged from 6% to 82%. These findings suggest that the particular mix of racial/ethnic groups in a community may differentially affect violent crime outcomes differently within and across communities. Moreover, GWR analyses of the effects of concentrated disadvantage and residential instability (available upon request) show that both predict violent crime to varying degrees, with a stronger effect for economic disadvantage which was significant in more neighborhoods when compared to instability. The local $R^2$ is higher in neighborhoods clusters near the lake in the east and lower in more inland areas. Since street gangs and gang-related violence have persisted over time in these communities (Sampson 2012; Sampson and Wilson 1995), this substantial criminogenic factor may be influencing ecological crime patterns in these areas.
Third, for Los Angeles (Figures 22e and f), the effects of residential instability also differ across the city, with criminogenic effects in lower income areas in south central neighborhoods, and no/very minimal effect in surrounding neighborhoods. Conversely, northern neighborhoods in the affluent Beverly Hills and Malibu areas actually have a negative relationship between residential instability and crime rates. The beta coefficient for the residential instability index ranged from -805 to 4,317, while the amount of variation explained (i.e., the local $R^2$) ranged from .001% to 86%. These results suggest that even though residents are moving in and out frequently in some areas of the city (i.e., residential instability), this does not have a criminogenic effect in very affluent areas since economic advantage may condition this relationship. Lastly, subsequent GWR analyses of the effects of concentrated disadvantage and racial/ethnic heterogeneity (available upon request) on violent crime show that both predict this outcome, with the magnitude of these effects varying based on the distance from the ocean.

By comparing the ways in which social disorganization theory operates in these three cities of low (Portland), moderate (Chicago) and high (Los Angeles) economic inequality, four results are important to highlight. First, based on the spatial distribution of crime in all three cities, Los Angeles has the highest incidence of crime and highest inequality, followed by Chicago, and then Portland. Second, while the effects of economic disadvantage are all positive across Portland neighborhoods, the effects of residential instability and population heterogeneity both have negative or positive effects depending on the particular tracts in Chicago and Los Angeles, respectively. Third,
Chicago and (to a greater degree) Los Angeles, have both a greater quantity of crime clusters and larger crime clusters.

Fourth, the variance explained in each model differs across cities (Figures 20f, 21f and 22f), with the highest local $R^2$ of .86 in Los Angeles, followed by the highest local $R^2$ of .82 for Chicago, and the highest local $R^2$ of .38 for Portland. Comparing the explained variance, these values suggest that social disorganization is best supported in a larger, more diverse and economically unequal metropolitan context (i.e., Los Angeles), when compared with a smaller, less dense, more economically homogenous metropolitan context (i.e., Portland). More broadly, while these four important results are likely due to differences in the total population and density, it also suggests that crime and social disorganization theory operates differently based on the city-level economic inequality and spatial locations (i.e., the particular tracts as shown in the GWR) subsumed within each city. Thus, spatial heterogeneity is certainly present in these models, and GWR can better model the effects of the structural social disorganization predictors on crime across space. Moreover, these results are consistent with those from Graif and Sampson (2009) on spatial heterogeneity in predictors of homicide, and more broadly suggest that the effects of structural predictors from criminological theories vary in their predictive ability both within counties and across counties.

In conclusion, this chapter first discussed the testing of institutional anomie theory using geospatial analysis methods across US counties. Next, it described the testing of

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42 While these explained variances differ across the three cities, it is important to note that the lowest $R^2$ is for the property crime outcome in Portland, while the two higher $R^2$ values were for the violent crime outcome in Chicago and Los Angeles. These results suggest that structural social disorganization predictors better predict violent crime when compared to property crime, which may be better explained within alternative frameworks such as routine activity theory (Cohen and Felson 1979).
social disorganization within and across US cities to better understand how the theory operates in three cities with widely varying levels of economic inequality. Lastly, geographically weighted regression was used to empirically model spatial heterogeneity and to compare how structural social disorganization predictors differentially affect crime outcomes in each of the three cities.
Chapter 6: Discussion and Conclusion

In this concluding chapter, I first discuss the empirical support for social disorganization theory and institutional anomie theory. Second, I describe the progress towards the integrated anomic disorganization theory based on the analyses in this dissertation. Third, I elucidate the theoretical, substantive and methodological contributions of this dissertation to the larger body of scholarly literature. Fourth, I describe the study limitations, as well as policy implications for academic researchers, criminal justice policymakers and law enforcement agencies. Fifth, I provide directions for future research on anomic disorganization theory and broader conclusions based on the theoretical and empirical findings in this dissertation.

1. Empirical Support for Social Disorganization Theory

The results from the main analyses show moderate to strong support for structural social disorganization predictors on property and violent crime outcomes (hypothesis 1) at the Census-tract level. Even when controlling for covariates of neighborhood crime, the effects of residential instability, economic disadvantage and racial/ethnic heterogeneity on both violent and property crime outcomes are significant. These findings contribute to the literature on social disorganization theory, since this study is one of the first to test the theory with such a large data set that includes more than 9,000 neighborhoods in 91 cities in major metropolitan areas. Moreover, the results from the multilevel analyses also support the robustness of these findings, since all three structural social disorganization predictors remain significant when introducing the county-level predictors from institutional anomie theory. This finding is an important contribution to research on neighborhood crime since it provides additional support for the criminogenic
effects of structural social disorganization predictors with a large sample of
neighborhoods across 83 metropolitan counties when controlling for additional
contextual effects of the institutional anomie predictors at the county level.

2. Empirical Support for Institutional Anomie Theory

The findings from the main and sensitivity analyses show moderate support for
the economic dominance concept in institutional anomie theory, with less support for the
crime-mitigating effects of the commitment to noneconomic institutions at the County-
level level. The important results to address in this section are threefold. First, the
bivariate correlations show that 6 of the 8 measures of economic dominance are
positively associated with both crime outcomes. Moreover, the multivariate regression
models also show consistent results when controlling for noneconomic institutions, in
that the Gini coefficient remains significant (prior to including control variables).

Importantly, the results comparing the six additional measures of economic
dominance on violent crime show varying levels of empirical support. Three measures
significantly predict violent and property crime prior to introducing control variables yet
are ordered with varying degrees of strength and explained variance (i.e., 1. Ricci-Schutz
Coefficient of Income Disparity, 2. Gini coefficient 3. Atkinson’s Measure of Income
Disparity). However, it important to note that these results are not replicated when
introducing control variables with each economic dominance measure. Therefore, these
results provide some support for the criminogenic effects of the economic dominance
(hypothesis 2) concept in institutional anomie theory on property and violent crime
outcomes using the largest sample size to date to test the theory, as well as using multiple
novel measures of economic dominance. They also replicate previous findings on the
criminogenic effects of economic dominance operationalized as the Gini coefficient, and suggest that the Gini Coefficient and Ricci-Schutz Coefficient are the best supported economic dominance measures (Baumer and Gustafson 2007; Maume and Lee 2003).

Second, the results for the crime-mitigating effects of the strength of commitment to noneconomic institutions (hypothesis 3) are less consistent and, in some cases, contrary to the hypothesized direction. Whereas there was more support for the crime-mitigating effects of a strong commitment to community, education, family, community and religion for violent crime, the effects for property crime were less consistent. Additionally, the effects of social welfare were positive for the violent crime outcome, which was contrary to expectations. In line with previous findings on institutional anomie theory (Baumer and Gustafson 2007; Maume and Lee 2003), this study shows that different measures of the strength of commitment to noneconomic institutions have differential effects on crime outcomes. The finding that the education system received greater empirical support is consistent with the original formulation of institutional anomie theory, which only included the institutions of the economy, education system, family and polity. Since education quality has been shown to affect criminal involvement (Deming 2011) and schools serve as primary source of socialization for children and adolescents, these results suggest that the more proximate institution of the education system may matter more for crime than other, more distal institutions such as religion or community. These results are also consistent with recent tests of institutional anomie theory (Weld and Roche 2017; Hövermann, Groß and Messner 2016), which also found that there was mixed evidence for the crime-reducing effects of noneconomic institutions. Moreover, the seemingly contradictory findings for the criminogenic effects of increasing
social welfare spending are consistent with Burek (2005) and Messner (1986), who found a positive relationship between public assistance spending and property crime. Thus, it is possible that public welfare assistance—paid on a monthly basis—may only provide for recipient’s needs for a portion of the month, after which they may commit property crime to obtain cash and goods readily convertible to cash.

Third and lastly, the findings on the moderating effects of noneconomic institutions on the relationship between the Gini coefficient and crime outcomes (hypothesis 4) showed that 7 of the 12 models were significant. For property crime, the significant interaction terms include the Gini Coefficient by social capital index, divorce rate and social welfare spending measures. For violent crime, the significant interaction terms include the Gini Coefficient by social capital index, divorce rate, voter turnout and social welfare measures. These results provide mixed support for the conditioning effects of noneconomic institutions on the criminogenic effects of economic dominance—a key theoretical argument of institutional anomie theory (Messner and Rosenfeld 2001; Messner, Thome and Rosenfeld 2008).

3. **Empirical Support for Anomic Disorganization Theory**

Based on the results of the multilevel models integrating variables from both theories, the significant findings provide tentative support for an integrated anomic disorganization theory of neighborhood crime. Therefore, there is mixed support for hypotheses 5, 5a and 5b, which state that: a) county-level economic dominance will moderate (i.e., amplify) the positive relationship between structural social disorganization predictors and neighborhood crime rates, and b) that the strength of commitment to noneconomic institutions will moderate (i.e., reduce) the positive relationship between
structural social disorganization predictors and neighborhood crime rates. However, it is important to note that the main effects of the Gini coefficient were only significant for neighborhood-level property crime, and most of the measures of county-level noneconomic institutions were not significant. It is possible that these non-significant effects could be due to the particular operationalization and measurement approaches in the dissertation, an issue that has been noted by other studies conducting tests of institutional anomie concepts (e.g., Bjerregaard and Cochran 2008; Piquero and Piquero 1998). These items are addressed in more detail later in this chapter in the sections on limitations and future research directions.

The primary support for this multilevel, integrated theory are the three statistically significant interaction effects between social disorganization predictors and institutional anomie theory predictors. These models suggest that neighborhood concentrated disadvantage is more criminogenic in a high economic inequality county-level context. They also show that residential instability may be less criminogenic in a high rate of religious adherence county-level context, and racial/ethnic heterogeneity may be less criminogenic in a high social capital context.

In particular, these significant moderation models are an important contribution to the literature on testing institutional anomie theory and theoretical integration more broadly for four reasons. First, these models show that the theory has tentative support for the interaction effects of structural predictors from two different theories at two different levels of analysis. More specifically, this empirical evidence suggests that county-level predictors play an important role in affecting the mechanisms by which structural social disorganization predictors influence both property and violent crime outcomes. Second,
this integrated theoretical model receives greater support for violent (vs. property crime) with a large sample of neighborhoods and counties in the United States over three years of data from more than 10 data sources. Third, these results show the application of the methodological approach of evaluating integrated theories with smaller ecological units (i.e., Census tracts) nested within larger ecological units (i.e., counties). This framework is effective and is a fruitful area of research (Krivo, Peterson and Kuhl 2009; Ramey 2013) for future inquiries or theory testing.

Fourth and most importantly, this theory makes steps towards developing a theory that attempts to explain a greater proportion of the variation\textsuperscript{43} in the dependent variable of interest: crime. It also demonstrates how this explained variance by theoretically-relevant variables can differ based on the larger macro-level context, as is shown in the geographically weighted regression analyses of the three case study cities of varying levels of economic inequality. By using the analytic model developed and tested in this dissertation, one can continue to add additional explanatory variables at the Census tract and county levels from existing datasets or primary data collection efforts. This integrated model can then be empirically tested to determine whether this addition of predictors from other theories increase the explained variance of the whole model.

4. Theoretical, Substantive and Methodological Contributions

This dissertation makes considerable theoretical, substantive and methodological contributions to the current body of scholarly literature. Theoretically, this dissertation makes progress towards developing and empirically testing an integrated theory.

\textsuperscript{43} The analyses in this dissertation are based on a negative binomial regression modeling approach, which yields different pseudo-R\textsuperscript{2} such as the McFadden’s R\textsuperscript{2} and other model fit statistics to estimate the explained variance. However, since OLS estimates of the R\textsuperscript{2} use a different calculation procedure, negative binomial pseudo-R\textsuperscript{2} statistics may underestimate the actual variance explained by the model (Long 1997).
encompassing social disorganization theory and institutional anomie theory. The significant moderation models between predictors from both theories provides some support for this integrated theory and shows how county-level institutional anomie can influence how structural social disorganization affects crime in neighborhoods. By using this theoretical framework, researchers can empirically test this proposed theory at multiple levels with actual data, expanding on the current analyses by using a larger sample of neighborhoods and counties (or other aggregate units). Moreover, the geospatial analyses of county-level crime and institutional anomie predictors, as well as social disorganization predictors in the three case study cities show that theoretical variables may receive varying empirical support in different ecological locations. This finding exhibits the concept of spatial heterogeneity (Graif and Sampson 2009; Arnio and Baumer 2012) and suggests that future tests of both theories and the integrated model should account for the fact that empirical support for theories may differ in different geographic contexts. Importantly, while empirical tests of social disorganization theory have discussed and accounted for spatial heterogeneity (Sampson 2012), no tests of institutional anomie theory have incorporated this concept, suggesting that this may be a fruitful avenue for future research.

Substantively, this dissertation provides a more complete and comprehensive assessment of crime at multiple levels of analysis, and in doing so, it has increased the understanding of predictors of crime. Although the explained variance was similar to previous findings, the multilevel framework can be used in the future with different measures to potentially increase the explained variance. By continuing to move towards the goal of explaining 100% of the variation in crime as the dependent variable, this study
makes progress towards better understanding the etiology and predictors of property and violent crime. To enhance the theoretical model and explained variance, future tests should use location-specific measures of additional predictors such as community gang activity or drug abuse/overdose rates, which could enhance the overall explained variance and yield a more comprehensive understanding of the causes of neighborhood crime and violence. More broadly, the geospatial results suggest that whereas some variables have global effects on crime across an entire city such as concentrated disadvantage, the effects of other theoretically-predictors such as residential instability vary greatly in their criminogenic effect, representing localized effects that differ based on the ecological location (i.e., neighborhood cluster) within the city. These findings are consistent with tests of social disorganization theory in different locations such as rural counties (Osgood and Chambers 2000) or an international context in The Hague in The Netherlands (Bruinsma et al. 2013), which show that empirical support for the structural social disorganization variables differs across ecological contexts.

Methodologically, this dissertation adds to the body of literature on institutional anomie theory. This is through testing it in the largest sample of counties to date, as well as testing the use of 8 different measures of economic inequality as shown in bivariate relationships with violent and property crime outcomes, and multivariate analyses with both crime outcomes. By introducing these additional novel measures of economic dominance that have not been previously tested in an institutional anomie theory framework with crime outcomes, the current study can inform future multivariate analyses using these alternative measures of economic inequality and dominance. The results on the additional economic dominance measures show that the Ricci-Schutz
Coefficient and Gini Coefficient were the best supported measures for both crime outcomes, whereas the Atkinson’s measure, Theil’s measure and Entropy index were also significant predictors of violent crime prior to adding control variables, and the coefficient of variation, squared coefficient of variation and Entropy index were significant predictors of property crime but in the opposite direction than expected.

Moreover, this dissertation builds on a trend in the literature towards using multilevel models for smaller aggregate units nested within larger aggregate units, while also providing moderate to strong support for social disorganization theory when using a multilevel modeling approach. This analysis could thus be extended to other aggregated macro-level units in nested structures such as neighborhoods within states, or states within countries. Furthermore, this dissertation contributes to the literature on institutional anomie theory by testing key concepts from the theory with new operationalization approaches, utilizing the largest sample of U.S. counties to date and novel measures of non-economic institutions within the theoretical framework, and examining both property and violent crime outcomes.

As a whole, this dissertation lays the theoretical and conceptual groundwork for future research on this proposed integrated theory. Specifically, the theory can be tested in broader applications to different levels of analysis (e.g., in an international and cross-national context). By testing the application and empirical support of this integrated theoretical framework, researchers can evaluate the generality of the theory across diverse samples and cultural contexts.
5. Study Limitations

Although this study makes important contributions to the literature on neighborhood crime and integrated theories, four limitations are important to discuss. First, due to data limitations in the National Neighborhood Crime Study, and in available secondary databases more broadly, no empirical measures are present for concepts such as collective efficacy, informal social control, social cohesion and social support. Moreover, there are no available measures of economic dominance such as survey items tapping the commitment to economic ends and availability of legitimate means to reach this goal. Additionally, measures such as the rate of religious adherence and divorce rate were used to operationalize commitment to religion and family, respectively, which may not fully tap the extent to which residents feel committed to noneconomic institutions in counties. Since such empirical data do not exist in large samples of neighborhoods or counties across the U.S., it is not possible to operationalize this concept using the approach of aggregating individual-level survey responses up to the ecological level. Moreover, a full synthetic theoretical integration (Tittle 1995; Tittle 2001) would require direct measures of these concepts, limiting the current dissertation to only providing a partial test of the proposed theoretical integration.

Second, since this study relies on existing data, some counties and Census tracts have missing data on crime outcomes due to limitations in reporting agencies and their lack of participation in crime reporting programs. This issue with missing data on such outcomes is widely documented (Marvell and Moody 1996) yet is still an important limitation to note. In this case, this limitation suggests that using victimization surveys

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44 In particular, the percentage of missing data was < 5% for counties, while the percentages of missing data was 16.7% for property crime and 18.2% for violent crime for Census tracts.
(Land 2007) as a validity and reliability test may be warranted in future analyses. Missing
data are also present for some of the explanatory variables as well (< 5% for both
counties and neighborhoods). Moreover, since the data were from 1999-2001 and utilized
the three-year averages for crime, with explanatory variables from 1997-2001, causal
order is tentative since not enough time may have elapsed for each independent variable
to have an effect on crime outcomes. Future empirical analyses will use additional data
on neighborhood crime from the year 2010 to determine how predictors measures 10+
years prior affect future property and violent crime rates. Third, since data on individual-
level attitudes towards pursuing economic ends over other goals in life is not available,
these measures were not incorporated into empirical models testing the proposed
integrated theory as a measure of the level of perceived anomie despite their key
theorized role. Fourth, since these data were limited to the United States setting, it was
not possible to empirically test how the theory may be supported in international
contexts.

6. Policy Implications

Based on this study’s findings, three potential policy implications are pertinent to
consider. First, government policymakers and criminal justice agencies should focus on
more distal causes (e.g., inequality, lack of community, underperforming schools) rather
than just on proximate causes (e.g., drug use, impulsivity, and other risky behaviors) of
crime. While these less direct economic and noneconomic factors may be less salient in
many targeted crime-reduction programs, they are very important in predicting crime and
should be taken into account when creating and critiquing policy. However, since studies
have shown support for more proximate factors such as alcohol availability (Nielsen and
Martinez 2003; Nielsen, Martinez and Lee 2005), racial profiling in policing (Dunham and Petersen 2017) and criminogenic places such as check cashing stores and pawn shops (Haberman and Ratcliffe 2015), policymakers should jointly consider the multiple levels of complex causes of crime and delinquency.

Second, law enforcement can take on a hotspots-policing approaches (Braga and Bond 2008; Weisburd et al. 2017) combined with a community policing approaches to enhance their effectiveness (Mastrofski, Worden and Snipes 1995). These specific strategies may be better able to use geospatial methods of examining crime patterning, while also enhancing the strength of community within neighborhoods and counties more broadly. Over time, such approaches can be combined with other successful community crime control programs such as neighborhood watch programs (Louderback and Sen Roy 2017) and surveillance cameras (La Vigne et al. 2011) to more successfully mitigate and prevent property and violent crime over time.

Third, researchers and policymakers should take both structure and culture into account when comparing community predictors of violent and property crime rates across neighborhoods. Since culture is an adaptation to one’s structural conditions (Kornhauser 1978), it is important for social policy to address neighborhood structural conditions such as poverty (Sampson 2012), single-parent families (Laub and Sampson 1988), and neighborhood disorder (Steenbeek and Hipp 2011), which can contribute to the development of gangs and deviant peer groups (Sampson and Wilson 1995). Indeed, the prescient guidance of Sampson and Wilson (1995:54) is still relevant today, who called on policymakers “to take a renewed look at social policies that focus on prevention…[and less]…after-the-fact (reactive) approaches that ignore the structural
context of crime and the social organization of inner cities.” Beyond the metropolitan areas discussed in their seminal work, the geospatial analyses of crime across US counties in this dissertation suggests that high crime clusters are located throughout rural and suburban areas in the US. Since much of this crime is driven by drug abuse including prescription opiates, heroin and methamphetamine (Felson and Staff 2017; Shannon, Perkins and Neal 2014), the results on these selected counties with high-high crime clustering can inform policies including targeted drug abuse education programs, harm-reduction approaches and increased access to treatment facilities.

7. Directions for Future Research

Drawing from the empirical findings and theoretical implications in this dissertation, future research can pursue four potential avenues. First, additional studies should obtain data on individual-level collective efficacy, informal social control and social cohesion across a greater number of US cities and neighborhoods. Using an econometric approach (Sampson 2012) and aggregating individual-level survey responses up to ecological areas such as Census blocks, Census tracts, neighborhood clusters, cities or even “egohoods” (Hipp and Boessen 2013: 287) could allow more valid and reliable measurement of key concepts including collective efficacy, anomie, economic dominance and the strength of commitment to noneconomic institutions. For example, in a few select years, the General Social Survey has included questions tapping individual’s levels of commitment to legitimate means and commitment to pursuing institutionalized goals which can be used to tap strain and to aggregate up to the metropolitan area (Baumer and

45 Unfortunately, these questions are not available for the years examined in this dissertation. Additionally, access to location identifiers for General Social Survey respondents are not available to the public (without extensive security protocols) due to confidentiality and anonymity concerns.
Gustafson 2007). Future studies could seek out these measures to operationalize the concept of economic dominance and future primary data collection efforts should consider adding similar survey questions for anomie and collective efficacy for multiple units of analysis at different levels of aggregation.

Second, geospatial analyses should be used more frequently to examine the institutional anomie theory and ways in which larger social structures (e.g., cities, counties and states) affect the neighborhoods located within such areas. By using innovative techniques such as geographically weighted regression (Andresen 2006), hot spots-cold spots analysis (Johnson and Bowers 2008), emerging hotspot analysis (Bunting et al. 2018), and risk terrain modeling (Kennedy, Caplan and Piza 2011), geospatial analyses can be used in the future to develop a more comprehensive understanding of the temporal and spatial patterning of crime. The results based on the use of interdisciplinary methodologies can then be used to inform law enforcement policies to better target high crime areas and to implement more effective crime prevention programs such as those based on risk terrain modeling (Kennedy, Caplan and Piza 2011).

Third, institutional anomie theory should be extended to smaller units of analysis such as neighborhoods to determine if the theory receives empirical support when testing it at different levels of analysis. The analytic issue of deciding on the correct unit of analysis for theory testing has been well documented by scholars (Hipp 2007; Matsueda 2017; Wooldredge 2002). Therefore, future tests of the anomic disorganization theory could even test institutional anomie predictors at the neighborhood-level and social
disorganization predictors at smaller units of analysis than neighborhoods (e.g., Census face blocks, blocks or block groups).

Fourth, future research should investigate the development of a more comprehensive integrated theoretical model including other major macro and micro-level theories with empirical data on the concepts that were unmeasurable in this dissertation to better test the proposed integrated theory. Specifically, future analyses may seek to test a three-level integrated model of social disorganization and institutional anomie theories with individuals (i.e., micro-level; level-1) nested within neighborhoods (level-2) nested within counties (level-3). This theoretical framework could follow a similar empirical specification to the integration of micro and macro-level variables described by Matsueda (2017) in his 2016 Sutherland Address at the American Society of Criminology Annual meeting. Furthermore, given similarities in the structural predictors between social disorganization and macro-level strain theory (Agnew 1999; Warner and Fowler 2003), these theories could also be integrated to better understand the main and interactive effects of community strain and social control on crime outcomes.

8. Conclusion

In conclusion, this dissertation provides strong empirical support for social disorganization theory and moderate support for institutional anomie theory. Based on the development of an integrated anomic disorganization theory, this new theoretical framework received moderate empirical support and should be tested with other measures of key concepts in future analyses. More broadly, this dissertation can inform the development of targeted strategies to reduce crime by focusing on more distal factors including improving the quality of social institutions, reducing poverty and residential
instability, and reducing the ever-increasing economic inequality between the rich and poor. By addressing these distal factors instead of only focusing on proximate factors such as militarized policing of minority neighborhoods, hard-on-crime incarceration approaches and strict barriers for individuals with criminal records, policymakers and society as a whole can benefit from greater reductions in crime and the resulting harm caused to victims.
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Figure 6: Map of Geographic Distribution of Three-Year Average Violent Crime Rate (per 100,000 population) for All Counties in the United States (1999-2001)
Figure 7: Map of Geographic Distribution of Gini Coefficient of Household Income for All Counties in the United States (2000)
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Figure 22: Geospatial Analyses of Crime in Los Angeles, California (a) Study Area (b) Spatial Distribution of Property Crime (c) Spatial Distribution of Violent Crime (d) Local Moran’s I of Violent Crime (e) GWR Beta Coefficient for Residential Instability from Social Disorganization Theory on Violent Crime (f) $R^2$ from GWR of SD Variables on Violent Crime
**APPENDIX B: Tables**

Table 1: Descriptive Statistics of Key Predictors and Control Variables at Neighborhood-Level and County-Level

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neighborhood-Level Crime Measures</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Three-year Average Property Crime Count</td>
<td>217.838</td>
<td>187.222</td>
<td>0.000</td>
<td>3320.000</td>
</tr>
<tr>
<td>Three-year Average Violent Crime Count</td>
<td>38.927</td>
<td>39.975</td>
<td>0.000</td>
<td>658.670</td>
</tr>
<tr>
<td>Three-year Average Property Crime Rate per 100,000</td>
<td>6562.191</td>
<td>8274.928</td>
<td>0.000</td>
<td>171739.130</td>
</tr>
<tr>
<td>Three-year Average Violent Crime Rate per 100,000</td>
<td>1176.438</td>
<td>1410.316</td>
<td>0.000</td>
<td>25633.800</td>
</tr>
<tr>
<td><strong>Neighborhood-Level Social Disorganization Measures</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Racial/Ethnic Heterogeneity Index</td>
<td>0.385</td>
<td>0.199</td>
<td>0.000</td>
<td>0.805</td>
</tr>
<tr>
<td>Concentrated Disadvantage</td>
<td>0.000</td>
<td>0.885</td>
<td>-1.607</td>
<td>4.359</td>
</tr>
<tr>
<td>Residential Instability</td>
<td>0.000</td>
<td>0.874</td>
<td>-2.213</td>
<td>2.742</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of Males Ages 15 to 24</td>
<td>7.286</td>
<td>3.483</td>
<td>0.000</td>
<td>44.200</td>
</tr>
<tr>
<td>Southern Location</td>
<td>0.321</td>
<td>0.467</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Total Population</td>
<td>3971.882</td>
<td>2122.317</td>
<td>301.000</td>
<td>23960.000</td>
</tr>
<tr>
<td>Percentage of New Immigrants</td>
<td>7.288</td>
<td>8.313</td>
<td>0.000</td>
<td>61.680</td>
</tr>
<tr>
<td><strong>County-Level Crime Measures</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Three-year Average Property Crime Count</td>
<td>3051.935</td>
<td>11346.136</td>
<td>0.000</td>
<td>289144.000</td>
</tr>
<tr>
<td>Three-year Average Violent Crime Count</td>
<td>403.179</td>
<td>2322.053</td>
<td>0.000</td>
<td>85982.000</td>
</tr>
<tr>
<td>Three-year Average Property Crime Rate per 100,000</td>
<td>2649.302</td>
<td>1537.827</td>
<td>0.000</td>
<td>12290.020</td>
</tr>
<tr>
<td>Three-year Average Violent Crime Rate per 100,000</td>
<td>288.588</td>
<td>284.474</td>
<td>0.000</td>
<td>4798.120</td>
</tr>
<tr>
<td><strong>County-Level Institutional Anomie Measures</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Measures of Economic Dominance</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Measure of Income Inequality</td>
<td>Value 1</td>
<td>Value 2</td>
<td>Value 3</td>
<td>Value 4</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td>Gini Coefficient</td>
<td>0.434</td>
<td>0.038</td>
<td>0.314</td>
<td>0.605</td>
</tr>
<tr>
<td>Ricci-Schutz Coefficient</td>
<td>0.309</td>
<td>0.029</td>
<td>0.217</td>
<td>0.439</td>
</tr>
<tr>
<td>Atkinson’s Measure</td>
<td>0.164</td>
<td>0.028</td>
<td>0.088</td>
<td>0.315</td>
</tr>
<tr>
<td>Theil Index</td>
<td>0.353</td>
<td>0.076</td>
<td>0.172</td>
<td>0.835</td>
</tr>
<tr>
<td>Coefficient of Variation of Income Disparity</td>
<td>1.030</td>
<td>0.194</td>
<td>0.605</td>
<td>2.394</td>
</tr>
<tr>
<td>Squared Coefficient of Variation of Income Disparity</td>
<td>1.098</td>
<td>0.457</td>
<td>0.367</td>
<td>5.732</td>
</tr>
<tr>
<td>Entropy Index</td>
<td>0.342</td>
<td>0.062</td>
<td>0.179</td>
<td>0.689</td>
</tr>
</tbody>
</table>

**Measures of Strength of Commitment to Noneconomic Institutions**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Value 1</th>
<th>Value 2</th>
<th>Value 3</th>
<th>Value 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social Capital Index</td>
<td>0.000</td>
<td>0.642</td>
<td>-1.940</td>
<td>3.536</td>
</tr>
<tr>
<td>Pupil to Teacher Ratio</td>
<td>14.941</td>
<td>2.568</td>
<td>5.500</td>
<td>30.700</td>
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**Control Variables**

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Table 2: Bivariate Correlations among All Variables Used in the Analyses at Neighborhood Level

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<td>6. Proportion of Males 15-24</td>
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<td>-.234**</td>
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<td>.065**</td>
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Note: ** Correlation is significant at the $p < 0.01$ level (2-tailed test). * Correlation is significant at the $p < 0.05$ level (2-tailed test).
Table 3: Bivariate Correlations among All Variables Used in the Analyses at County Level

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<td>.987**</td>
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<td>9. Entropy Index</td>
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<td>1.000**</td>
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<td>.046*</td>
<td>.044*</td>
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<td>.027*</td>
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<td>.229**</td>
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<td>13. Voter Turnout</td>
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<td>-.332**</td>
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<td>-.316**</td>
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<td>.086**</td>
<td>-.004**</td>
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<td>.148**</td>
<td>.137**</td>
<td>.121**</td>
<td>.106**</td>
<td>.148**</td>
<td>.220**</td>
<td>-.299**</td>
<td>-.147**</td>
<td>.025**</td>
<td>-.081**</td>
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</tbody>
</table>

Note: Control variables including the proportion of males 15 to 24, percentage black, percentage Hispanic/Latino, unemployment, and southern location are omitted in this correlation table due to space limitations.

Note: ** Correlation is significant at the $p < 0.01$ level (2-tailed test). * Correlation is significant at the $p < 0.05$ level (2-tailed test).
Table 4: One level Negative Binomial Models of Census-tract Social Disorganization and Three-year Average Crime Counts

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<td>(se)</td>
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<td>irr</td>
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<td>Neighborhood-Level Social Disorganization Measures</td>
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<tr>
<td>Racial/Ethnic Heterogeneity Index</td>
<td>.033 (.040)</td>
<td>.260** (.040)</td>
<td>.155** (.044)</td>
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<td>Concentrated Disadvantage Index</td>
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<td>.164** (.009)</td>
<td>.794** (.010)</td>
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<td>Residential Instability Index</td>
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<td>.356** (.009)</td>
<td>.208** (.010)</td>
<td>.254** (.011)</td>
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<tr>
<td>Proportion of Males Ages 15 to 24</td>
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<td>-.025** (.002)</td>
<td>-.025** (.002)</td>
<td>.976 (.015)</td>
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<tr>
<td>Southern Location</td>
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<td>.087** (.018)</td>
<td>.087** (.018)</td>
<td>1.091 (.018)</td>
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<td>Percentage of New Immigrants</td>
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<td>-.008** (.001)</td>
<td>-.008** (.001)</td>
<td>.992 (.001)</td>
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<td>R²</td>
<td>.014</td>
<td>.019</td>
<td>.074</td>
<td>.077</td>
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<td>alpha (α)</td>
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Note: ** Statistically significant effects, p < 0.01, two-tailed test * Statistically significant effects, p < 0.05, two-tailed test. The results in this model are unstandardized regression coefficients, standard errors (in parenthesis) and incident rate ratios. All models account for the Census-tract population by including an exposure variable of the Census-tract population. The R² reported is McFadden’s pseudo R².
Table 5: One level Negative Binomial Models of County-level Institutional Anomie and Three-year Average Crime Counts

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<td>Gini Coefficient of Income Inequality</td>
<td>5.598** (0.593) 269.886</td>
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<td>1.431 (0.882) 4.183</td>
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<td>0.125** (0.043) 1.134</td>
<td>0.129** (0.043) 1.138</td>
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<td>(per 1,000)</td>
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Note: ** Statistically significant effects, p < 0.01, two-tailed test; * Statistically significant effects, p < 0.05, two-tailed test. The results in this model are unstandardized regression coefficients, standard errors (in parenthesis) and incident rate ratios. All models account for the county population by including an exposure variable of the county population. The R² reported is McFadden’s pseudo R².
Table 6: One level Negative Binomial Models of County-level Institutional Anomie and Three-year Average Crime Counts Comparing Different Measures of Economic Dominance

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Note: ** Statistically significant effects, $p < 0.01$, two-tailed test; * Statistically significant effects, $p < 0.05$, two-tailed test. The results in this model are unstandardized regression coefficients, standard errors (in parenthesis) and incident rate ratios. All models account for the county population by including an exposure variable of the county population. The R² reported is McFadden’s pseudo R².
Table 7: One level Negative Binomial Models of County-level Institutional Anomie and Three-year Average Crime Counts with Gini Coefficient by Strength of Commitment to Noneconomic Institutions Interaction Terms

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<td>Percentage Unemployed</td>
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<td>0.044*</td>
<td>0.053**</td>
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<td>0.137**</td>
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<td>0.231**</td>
<td>0.255**</td>
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<td>.007</td>
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Note: ** Statistically significant effects, *p < 0.01, two-tailed test; * Statistically significant effects, *p < 0.05, two-tailed test. The results in this model are unstandardized regression coefficients, standard errors (in parenthesis) and incident rate ratios. All models account for the county population by including an exposure variable of the county population. The R² reported is McFadden’s pseudo R². The value of the incident rate ratio for the Gini Coefficient X Voter Turnout Interaction (1137109.416) was too large in value and was thus omitted from the table.
Table 8: Multilevel Models of Census-tract Level Social Disorganization Measures and County-level Institutional Anomie Measures on Census Tract-Level Three-year Average Crime Count with Tract Population Exposure

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<tr>
<td>Racial/Ethnic Heterogeneity Index</td>
<td>0.189** (.052)</td>
<td>0.349** (0.053)</td>
<td>0.181** (0.044)</td>
<td>0.280** (0.044)</td>
<td>0.194** (0.045)</td>
<td>0.283** (0.086)</td>
<td>0.616** (0.086)</td>
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<td>(1.198)</td>
<td>(1.323)</td>
<td>(1.214)</td>
<td>(1.326)</td>
<td>(1.852)</td>
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<td>Concentrated Disadvantage Index</td>
<td>0.139** (0.011)</td>
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<td>0.652** (0.009)</td>
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<td>0.631** (0.009)</td>
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<td>(1.919)</td>
<td>(1.697)</td>
<td>(1.927)</td>
<td>(1.880)</td>
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<td>0.306** (0.012)</td>
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<td>0.178** (0.011)</td>
<td>0.195** (0.011)</td>
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<td>Residential Instability X Religious Adherence Rate</td>
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<td>-0.001** (.000)</td>
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<td>Racial/Ethnic Heterogeneity X Social Capital Index</td>
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<td></td>
<td>0.594** (0.187)</td>
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<tr>
<td>Proportion of Males Ages 15 to 24</td>
<td>-0.010** (0.003)</td>
<td>-0.010** (0.002)</td>
<td>-0.012** (0.002)</td>
<td>-0.012** (0.003)</td>
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<td>(0.989)</td>
<td>(0.989)</td>
<td>(0.988)</td>
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<tr>
<td>Southern Location</td>
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<td>-0.165 (0.164)</td>
<td>-0.127 (0.197)</td>
<td>-0.153 (0.196)</td>
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<td>Percentage of New Immigrants</td>
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<td>0.848</td>
<td>0.881</td>
<td>0.858</td>
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<tr>
<td></td>
<td>-0.016** (0.001)</td>
<td>-0.010** (0.001)</td>
<td>-0.011** (0.001)</td>
<td>-0.009** (0.001)</td>
<td>-0.009** (0.001)</td>
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**County-Level Institutional Anomie Measures**

**Measures of Economic Dominance**

<table>
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<tr>
<th>Gini Coefficient of Income Inequality</th>
<th>5.079** (1.644)</th>
<th>4.291** (1.630)</th>
<th>3.804 (2.485)</th>
<th>4.306 (2.652)</th>
<th>0.644 (2.499)</th>
<th>3.930 (2.661)</th>
<th>4.938 (2.640)</th>
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<td>160.676</td>
<td>73.022</td>
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<td>1.904</td>
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**Measures of Strength of Commitment to Noneconomic Institutions**

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<th>Social Capital Index</th>
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<th>0.000 (0.130)</th>
<th>-0.180 (0.178)</th>
<th>-0.121 (0.210)</th>
<th>-0.182 (0.177)</th>
<th>-0.123 (0.211)</th>
<th>-0.123 (0.230)</th>
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<td>0.939</td>
<td>1.000</td>
<td>0.835</td>
<td>0.886</td>
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<td>0.84</td>
<td>0.67</td>
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<th>Pupil to Teacher Ratio</th>
<th>-0.063** (0.019)</th>
<th>-0.049** (0.018)</th>
<th>-0.029 (0.028)</th>
<th>-0.019 (0.029)</th>
<th>-0.021 (0.025)</th>
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<td>0.939</td>
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<th>Voter Turnout</th>
<th>1.057 (0.777)</th>
<th>0.318 (0.794)</th>
<th>1.192 (1.155)</th>
<th>-0.351 (1.331)</th>
<th>-0.513 (1.110)</th>
<th>-0.394 (1.336)</th>
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<td>2.878</td>
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<th>Divorce Rate (per 1,000)</th>
<th>0.006 (0.007)</th>
<th>0.002 (0.007)</th>
<th>0.016 (0.010)</th>
<th>0.005 (0.012)</th>
<th>-0.002 (0.010)</th>
<th>0.005 (0.012)</th>
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<tr>
<th>Social Welfare Spending per Person</th>
<th>0.001 (0.002)</th>
<th>-0.005 (0.003)</th>
<th>0.005 (0.003)</th>
<th>0.003 (0.004)</th>
<th>0.005 (0.004)</th>
<th>0.003 (0.004)</th>
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<th>Religious Adherence Rate (per 1,000)</th>
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<th>-0.001** (0.000)</th>
<th>0.000 (0.001)</th>
<th>0.000 (0.001)</th>
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**County-level Control Variables**

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<th>Percentage Black</th>
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<td>Percentage Hispanic/Latino</td>
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<td>0.999</td>
<td>-0.005</td>
<td>(0.007)</td>
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<td>Percentage Unemployed</td>
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<td></td>
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<td>1.178</td>
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<tr>
<td>uo (d.f.)</td>
<td>.083** (75)</td>
<td>.063** (72)</td>
<td>.179** (64)</td>
<td>.164** (61)</td>
<td>.163** (58)</td>
</tr>
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</table>

Note: ** Statistically significant effects, \( p < 0.01 \), two-tailed test; * Statistically significant effects, \( p < 0.05 \), two-tailed test. The results in this model are unstandardized regression coefficients, standard errors (in parenthesis) and event rate ratios. All models account for the Census-tract population by including an exposure variable of the Census-tract population. Each model contains the final estimation of the variance components as indicated by \( u_o \) (d.f.).
REFERENCES


Bunting, Ryan P., Oliver Chang, Christopher Cowen, Richard P. Hankins, Staci Langston, Alexander F. Warner, Xiaxia Yang, Eric R. Louderback, and


and Psychological Functioning in Adults with Mild Intellectual Deficits."


VITA

Eric R. Louderback earned his Ph.D. in Sociology in 2018 at the University of Miami with concentrations in Criminology and Medical Sociology. His research interests include the testing and integration of macro-level crime theories, geospatial analysis of neighborhood crime patterns, predictors of cybercrime, cognitive decision-making in cyberspace, and recent advances in quantitative statistical analysis methods. He is currently working on projects investigating sociotechnical predictors of cybercrime victimization and offending using multilevel survey data within a large institutional context. His research studies have appeared in peer-reviewed journals including the Journal of Research in Crime and Delinquency, The British Journal of Criminology and The Professional Geographer.