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Defining Neighborhood: Social Disorganization Theory, Official Data, and Community Perceptions

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DEFINING NEIGHBORHOOD:
SOCIAL DISORGANIZATION THEORY, OFFICIAL DATA,
AND COMMUNITY PERCEPTIONS

by

Jeremy Waller
Bachelor of Arts
University of Nevada, Las Vegas
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May 2012
ABSTRACT

Defining Neighborhood: Social Disorganization Theory, Official Data, and Community Perceptions

by

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While the theory of social disorganization has been refined through research and critique, data and methods used to measure key concepts related to the theory have largely remained the same. This study examines the extent to which resident perceptions of neighborhoods are reflected similarly in official data provided by the U.S. Census, in terms of both neighborhood boundaries and neighborhood conditions. It consists of a combination of respondent-identified data and official data gathered on neighborhoods, their condition, and crime. Comparisons between perceptual indicators of neighborhood boundary and characteristics and corresponding official data at the block, block group, and Census tracts are made. Path models of social disorganization are also developed, using both perceptual and official data collected in 2010 among Las Vegas, Nevada residents. Results demonstrate whether perceptual models that predict crime and delinquency outperform traditional models of social disorganization. This exploratory research has the potential of affecting the way social disorganization-related research is conducted in the future, by providing reasonable evidence for the need of alternative measures of neighborhood and its conditions.
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CHAPTER 1  
INTRODUCTION

The study of humans and how they create and interact with their environment was the basis for Park and Burgess's *The City* (1925), which laid the early foundation for what would later become social disorganization theory. Borrowing ideas from human ecological theory, Park and Burgess suggested that metropolitan environments shared common instinctual triggers within humans, much in the same way as animals share with natural environments. As stated by Park and Burgess (1925), “The consequence is that the city possesses a moral as well as physical organization, and these two mutually interact in characteristic ways to mold and modify one another” (p. 4). The ecological foundation of Park and Burgess’ work shifted focus for criminal justice researchers from looking at types of people and crime, to looking at types of places and crime. The original social disorganization theory purported that a neighborhood’s characteristics can be shaped by a multitude of factors, which play a role in the community’s level of social organization. This organization, in turn, influences the amount of social control the neighborhood possesses over its residents, and thus influences the level of crime and decay within that neighborhood.

Over seven decades have passed since Shaw and McKay published their work *Juvenile Delinquency and Urban Areas* (1942), establishing the beginnings of the theory of social disorganization. The theory, which attempts to explain neighborhood decay and criminal activity with both internal and external factors, focuses not on the criminal but on the world around which he lives. According to the original theoretical model, a neighborhood's level of organization can be affected by three structural factors (Shaw &
McKay, 1942). These include a neighborhood’s level of socioeconomic status, its ethnic heterogeneity, and its level of residential mobility. Each of these factors contributes in differing ways to a community’s inability to self-regulate, which can result in increased crime and delinquency.

Social Disorganization

The theory of social disorganization represented a paramount shift in the way criminologists looked at crime and its catalysts. However, while it did much in changing perspectives, further empirical research revealed some glaring issues that hindered its usefulness. In fact, a multitude of criticisms left it all but irrelevant well into the 1980s (Bursik, 1988). Part of this criticism centered on the inability to directly link the original exogenous variables to crime and delinquency (Kornhauser, 1978). The original theoretical model revolved solely around its three structural variables, and while these three variables did play a part in the relationship between a neighborhood’s organization and crime, a direct link proved difficult to demonstrate (Kornhauser, 1978).

Later, authors would reveal that several factors intervened in this relationship, with the three original exogenous variables contributing to the development of other endogenous factors that would then affect a community’s ability to self-regulate (Bursik, 1988; Kornhauser, 1978). When developing the first full empirical test of the theory, Sampson and Groves (1989) offered a more complete social disorganization model. Referencing the work of Kornhauser (1978), who said there were several endogenous variables that intervened in the relationship between the original structural variables and crime and delinquency, researchers developed a model to effectively test the original structural variables’ effects on these endogenous factors, and in turn their group effect on
crime and delinquency (Sampson & Groves, 1989). In essence, Sampson and Groves (1989) argued that the three exogenous variables identified in the original model (i.e., SES, racial heterogeneity, and residential mobility) contribute to the creation of certain intervening variables, which they identified as local social ties, unsupervised teenage peer groups, and organizational participation. These three intervening variables are commonly referred to as ‘collective efficacy’.

**Collective Efficacy**

Within the context of social disorganization, collective efficacy is comprised of two dimensions, a neighborhood’s level of social control and its level of social cohesion (Bursik & Grasmick, 1993; Lowenkamp, Cullen, & Pratt, 2003; Sampson & Groves, 1989; Sampson, Raudenbush, & Earls, 1997; Veysey & Messner, 1999). Sampson (2004), defined collective efficacy as, “a task-specific construct that draws attention to shared expectations and mutual engagement by residents in local social control” (p. 108). Shaw and McKay were specific in their claims that teenage peer groups had a large influence over the crime and delinquency within a community. Left unsupervised, teenage peer groups could negatively affect a community’s level of social organization (Shaw & McKay, 1969; Sampson & Groves, 1989). There are other instances, such as the prevention of general crime and property theft, where social control can be helpful in creating a socially organized environment (Sampson, 2004). Therefore, a community’s level of social control was identified as an important aspect of collective efficacy.

Social cohesion is defined as a summary of a community’s trust, altruism amongst neighbors, and common values. It is this social cohesion that fosters an environment friendly to mutual social control. If the neighbors trust in one another, and are expected
to help each other in times of need and in the interest of shared values, then the social control in a neighborhood is increased (Sampson, 2004). For example, residents might participate regularly in a neighborhood watch program to ensure their community’s safety. They might also meet regularly to socialize with neighbors in their community, forming a network of bonds and friendships which serve to increase their shared beliefs and values. Each of these actions contributes to the level of social cohesion, and in turn social control, by building trust and mutually shared interests within a community which result in an increased likelihood that residents will act to protect and maintain those shared values.

Unlike the structural determinants of social disorganization, which are often measured using U.S. Census data, ‘collective efficacy’ is often measured using surveys administered at the local level, with various indicators used to measure this important concept. Questions are formulated with regards to dimensions of collective efficacy, with emphasis being given to a community’s level of control and supervision over teenage peer groups, its level of organizational participation, and the prevalence of local friendship networks (Sampson, Raudenbush, & Earls, 1997). Local friendship networks are often gauged by asking respondents a series of questions related to their formation of such networks. Questions such as how well respondents know neighbors in their community, how often respondents get together with members of their community, and how long respondents have lived in their neighborhood are common survey questions used to measure collective efficacy. Organizational participation is commonly measured using questions related to how often respondents participate in community organizations and meet with neighbors. Finally, the level of social control is frequently measured using
questions related to how likely it would be for neighbors to intervene in a variety of hypothetical scenarios (e.g., breaking up a fight, putting out a fire, disciplining unruly children, etc.) (Sampson, 2004).

Collective efficacy shares a careful relationship with the exogenous variables identified in the original social disorganization model. Specifically, communities with lower socioeconomic status predominantly display decreased levels of organizational participation and community involvement. Communities with higher ethnic heterogeneity (i.e., racial diversity) tend to have increased feelings of isolation and alienation due to mistrust. As a result, members of these neighborhoods are less likely to develop strong social bonds (Sampson & Groves, 1989). Finally, more densely populated areas and neighborhoods in which residents move in and out frequently show higher rates of crime because of decreased feelings of responsibility for the area (Park & Burgess, 1925). The presence of these characteristics would likely lead to further breakdowns in informal social control and a subsequent increase in crime and delinquency.

In addition to the inclusion of endogenous factors, contemporary tests of social disorganization theory acknowledge the importance of two additional structural variables: urbanization and familial disruption (Sampson & Groves, 1989; Sampson, 1987). Familial disruption, or families experiencing the loss of an essential family member due to divorce or separation, has been found to contribute to a break down in social control. With a familial unit being less stable, it is likely to affect the amount of supervision possible in the neighborhood, allowing for groups of delinquents to go about without proper social control (Sampson, 1987; Sampson & Groves, 1989). Urbanization, defined
as the urban environmental make up of a community, was added due to its link with loosened social controls when compared to rural and suburban areas. The anonymity of urban environments may make the formation of friendship networks less likely and also strongly hinder any participation in community organization events (Fischer, 1982; Sampson & Groves, 1989; Shaw & McKay, 1969).

Testing Social Disorganization Theory

Sampson and Groves (1989) offered the first formal test of social disorganization theory, modeling the effects of both the neighborhood structural determinants and the endogenous characteristics of neighborhoods on crime and delinquency (Figure 1). The researchers tested the theory using data collected via the British Crime Survey (BCS), a nationwide survey that gathers both descriptive and qualitative data from citizens in Great Britain. Results from over 230 communities showed a promising relationship between the variables identified as being linked to a community’s social organization level and crime and delinquency. Analysis revealed that communities possessing “sparse friendship networks, unsupervised teenage peer groups, and low organizational participation had disproportionately high rates of crime and delinquency” (Sampson & Groves, 1989, p. 799). Of even higher consequence, the endogenous factors identified by researchers were found to mediate a sizeable portion of the relationship between the structural factors of social disorganization and crime and delinquency. Furthermore, it marked the first instance where representative data was used in measuring these variables. In the past, obtaining data that represented the five exogenous factors was simply too costly and large of a task for previous researchers (Bursik, 1988; Bursik & Grasmick, 1993; Sampson & Groves, 1989). It was also paramount in that formal tests took into consideration the
endogenous intervening variables that researchers held key in the relationship between a neighborhood’s social disorganization and crime and disorder.

When replicating Sampson and Groves’s (1989) study of social disorganization in the United States, researchers traditionally rely on U.S. Census data for measures of neighborhood condition. Census data are attractive to researchers because they provide detailed and complete information about the entire population of the United States (Stark, 1997; Roh & Cho, 2008). The U.S. Census traditionally divides cities into

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1 Traditionally, a path model is used to test Sampson and Groves (1989) extended model of Social Disorganization. In a path model, each exogenous variable is individually linked to each endogenous intervening variable. However, this figure represents the causal model of Social Disorganization as presented by Sampson and Groves (1989). For an example of the path model, like the one used by Sun, Triplet, and Gainey (2004) see Figure 3.
various sub-units representing official geographic boundaries for the collection and organization of data (U.S. Census Bureau, 2010). For example, cities or Metropolitan Statistical Areas (MSAs) are divided into tracts, tracts into block groups, and block groups into blocks. A multitude of descriptive information is collected from each of the different levels, and in some cases all the way down to the lowest, block level. This includes demographic information such as population and race, and also information on occupation and education level. However, due to feasibility and cost, more detailed information is only collected down to the block group level. For example, information such as income, education level, and occupation (i.e., the type of indicators used for measuring variables of social disorganization), are only available at the larger tract and block group levels.

Defining Neighborhood

Through the use of scientific inquiry, our understanding of the link between social disorganization and crime and disorder has increased significantly throughout the past few decades. Researchers have looked at a multitude of measures for both the exogenous and the intervening predictors of crime and delinquency, while at the same time increasing the overall scope of the theory. Despite these advancements, one aspect of the theory has remained a constant: the use of official boundaries as a proxy measure of neighborhood (i.e., census tracts or block groups) (Bursik & Webb, 1982; Sampson & Groves, 1989; Schuerman & Kobrin 1983; Sun, Triplett, & Gainey, 2004; Taylor & Covington, 1988).

Researchers have been able to identify what defines an “organized neighborhood” in terms of concepts conveyed, but relatively little work has been undertaken to measure
how individuals actually define what constitutes the neighborhood or community in which they live (Sampson & Groves, 1989; Shaw & McKay, 1969). Research in the area of social disorganization has relied on one of four types of official data to define neighborhood boundary: local community areas, census boundaries, police beats, and electoral wards (Bursik & Grasmick, 1993). Researchers divide and study communities based on relatively arbitrary official boundaries, which we largely assume serve as a valid indicators of neighborhood dynamics. However, the amount of research questioning this assumption has grown, leading some to believe that the past methods relying on census data may be inadequate (Boggess & Hipp, 2010; Bursik, 1988; Grannis, 1998; Sampson & Groves, 1989). For example, Kubrin and Weitzer (2003) call into question the “inexact correspondence between census tract boundaries and the ecological factors that shape social interaction”, and note that it is an issue yet unaddressed by research (p. 394). Boggess and Hipp (2010) also admit the limitation of measurement at the tract level in their paper determining whether violent crime and residential mobility still share the same relationship in minority communities, stating:

Like many studies before us, we are constrained by data availability; in this case, our indicator of neighborhood crime was only available at the reporting district level, which is essentially analogous to the census tract. We therefore used census tracts as our proxy for neighborhoods (p. 357).

The authors point out the lack of a proper measure, but like many others before them, simply conclude that there are few alternatives.

Further Limitations of Official Data

Administrative boundaries present a problem for research due to their arbitrary creation. The U.S. Census Bureau notes that census lines are determined by host of different visible features, which include urban structures like streets and power lines, as
well as natural barriers such as rivers and ridge lines in the absence of other alternatives (U.S. Census Bureau, 2000). While permanent features such as these might serve as a competent guide for the drawing of physical boundaries, these features ignore human interaction and social networks as they pertain to neighborhood creation. Seeing this, some researchers have attempted to better connect official boundaries to the networks that they contain, such as Schuerman & Kobrin (1983). In their study, Schuerman and Kobrin (1983) grouped together census tracts that shared demographic information such as population and racial heterogeneity, and also took into account each tract’s crime rate. This effort was aimed at obtaining a better proxy for neighborhood, but researchers found that it no better addressed the inherent issues with administrative boundaries than the ungrouped boundaries themselves (Bursik & Grasmik, 1983).

Many examples can be found within the literature that question the validity of using administrative boundaries as indicators for neighborhood. For example, Grannis (1998) questions the traditional measurements of neighborhoods and their dividers in an article exploring the physical composition of neighborhood streets and how they divide race and class. Within this context, Grannis quotes Rabin (1987), “one could look from streets in a black neighborhood across a fifty foot wide patch of trees and underbrush to a continuation of the same streets in an adjacent white neighborhood” (p. 219). This would mean that it is entirely possible for a white upper class community to be within a hundred or so feet of an ethnically diverse lower class neighborhood. In this case, it would be unlikely that the two neighborhoods would share any traits in common on a social organization level; and yet, if the two neighborhoods shared grouping within common
visible features, administratively defined boundaries might deem them essentially the same “neighborhood”.

An example of these limitations in an applied criminal justice setting can be found in hot spot research. Past research on hot spot analysis often indicates that very small sections of a city are responsible for generating the majority of crime hot spots, such as a portion of a street or a few households (Smith, Franzee, & Davison, 2000; Weisburd & Eck, 2004; Sherman, Gartin, & Buerger, 1989). However, because of the arbitrary nature of administrative boundaries, it is likely that completely separate neighborhoods with conflicting conditions could be grouped together into the same tract and thus be defined simply as one “community” or “neighborhood”. In his book, “From the Ground Up”, Grannis (2009) makes his thoughts against the use of administrative boundaries as a definition of neighborhood clear, “I have argued that neighborhood communities are geographically identifiable because the networks of interactions that produce them, that translate neighbor-level interactions into neighborhood communities, are constrained by predictable urban geographic substrates. Administrative units are not those substrates” (p. 192).

Grannis (2009) explored this apparent disconnect between neighborhoods and their administratively defined boundaries, by asking respondents in a study to draw their neighborhood on a map and select the homes of their friends or acquaintances within that neighborhood. Residents were found to associate their own neighborhoods dependent upon an identifiable subset of personal network relations within a defined section of tertiary streets rather than any particular administrative barrier. The design of tertiary streets were often found to encourage or restrict the formation of these network relations
and thus form and shape a respondents’ definition of neighborhood. The same did not hold true for administrative boundaries, however, which had little effect on respondent definitions (Grannis, 2009).

Finally, the most widely recognized name in contemporary social disorganization theory research, Robert Sampson, questioned the validity of official data as a proxy measure of neighborhood when he provided the opening remarks at NIJ’s 11th Crime Mapping Research Conference in Miami, Florida. He stated, “There is no clear definition of neighborhood because the term neighborhood means different things to different people” (Sampson, 2011). This sentiment uncovers precisely the problem with administrative boundaries used as a proxy for neighborhood: it lacks their foundation within the networks of humans that it is supposed to represent.

To summarize, social disorganization theory is a highly popular theory in the field of criminology. The theory is strongly rooted in the neighborhood dynamic, how a community interacts with one another and their environment. However, the concept of neighborhood is complex and difficult to conceptualize, so official data is often used as a proxy measure. The addition of endogenous variables recognizes the importance of individual interactions, even though the crux of the theory is macro-level. However, additional research is needed to determine whether official measures of neighborhood are valid measures in the social disorganization context. This study aims to explore this question by comparing respondent-provided perceptual data relevant to social disorganization to official data to determine whether the two are similar.
CHAPTER 2
CURRENT STUDY

The current study builds on the existing literature in three distinct ways. First, it determines the level of consistency between official administrative boundaries commonly used as proxies for neighborhoods in social disorganization research with perceptual boundaries of neighborhoods. Perceptual boundaries of neighborhoods are compared to official boundaries at the block, block group, and tract level, and consistency between the two are gauged in terms of both count and area\(^2\), using a geographic information system (GIS). Second, official neighborhood structural determinants of social disorganization contained in U.S. Census data, and aggregated to the geographic level that is most consistent with perceived neighborhood boundaries, will be compared to corresponding perceptual measures of neighborhood condition. Comparisons between these two measures will be made in order to determine whether official measures of exogenous structural determinants of social disorganization are valid indicators of neighborhood condition. Third, the current study models the effects of social disorganization on three crime categories using traditional measures of neighborhood structure and collective efficacy. Results of these models are then compared to results of models using perceptual measures. Model comparisons are made in order to determine whether perceptual models outperform traditional models in their ability to explain crime.

\(^2\) See Chapter 3: Methods and Measures for a complete detail of how neighborhoods were measured, as well as Chapter 4: Analytical Approaches for a detail of the complete analysis and its construction.
Research Hypothesis

In light of existing research that questions whether official data serve as valid indicators of what individuals perceive as their neighborhood, the current research tests the following three hypotheses. Stated formally, they are:

1. Official census boundaries of neighborhood (measured at the block, block group, and tract level) are inconsistent with the perceptual boundaries of neighborhood, either in terms of the number of each geographic unit or in terms of the area that each unit comprises.

2. Each of the official measures of neighborhood structural condition that characterizes social disorganization is dissimilar to corresponding perceptual measures.

3. Perceptual models of social disorganization outperform traditional models in terms of their ability to explain variation in levels of crime.

This current study is important for several reasons. First, results from tests of the first hypothesis will shed light on whether the long-standing practice of using official administrative boundaries as proxies for neighborhoods is appropriate. Further, if official measures of the neighborhood structural condition associated with social disorganization are not similar to corresponding perceived measures, then it calls into question the validity of commonly used data to examine the theory. Finally, this study is important because it offers insight into an alternative approach of explaining crime, an approach that assumes the formation of social bonds is a function of residents’ perceptions of their neighborhood. In summary, the current study is important because results produced from it will guide future research interested in understanding the relationship between social disorganization and crime and delinquency.
CHAPTER 3

METHODS AND MEASURES

The current project involved both survey research and secondary data analysis. First, survey data were collected as part of the “Perceived Versus Official Measures of ‘Neighborhood’ and Social Disorganization: Assessing the Validity of Commonly Used Indicators” study approved by UNLV’s Institutional Review Board (IRB #1009–3583M). The surveys were administered in 2010 to a convenience sample of 116 respondents, age 18 to 60, living in Clark County, Nevada. The survey consisted of two data collection phases. Details of both phases of the project, the secondary data obtained from the U.S. Census Bureau, and local law enforcement agencies are described in the following sections.

Perceptual Measures

Boundary

Perceptual measures used in the current study were collected during a two-phase survey. Phase one of the study involved respondents interacting with a geographic information system (GIS) in order to measure the perceptual boundaries of their neighborhoods. Specifically, each respondent provided researchers with their residential address, which was entered into mapping software, in order to produce an address point located on an aerial map image of their home and surrounding area, displayed at a 1:10,000 resolution. Next, respondents were provided instructions on how to manipulate the map that was produced (i.e., zoom the map image in/out, how to pan from location to location, and how to use a mouse to draw on the map image). Then respondents were asked to position the map image to where they could see their neighborhood. Finally,
Figure 2. A screen capture illustrating a respondent’s neighborhood boundary.³

they were instructed to use the mouse to draw a single, continuous line around the area on the map that represented their neighborhood.⁴ Figure 2 provides an image that illustrates the end result of this process.

When finished, the resulting polygon was exported as a shapefile and saved under the respondent’s unique identifier. Table 1 provides summary statistics for the measure of respondents’ perceived neighborhood boundaries and shows the size of neighborhoods ranged from as small as less than one-one hundredth of a square mile to larger than 10mi², with the average neighborhood being .29mi².

³ Census boundaries provided for readership only. Boundaries were not displayed when respondents outlined their neighborhood for the study.
⁴ See Appendix B for survey instructions, Part 1.
Table 1

*Descriptive Statistics for Perceptual and Official Boundary Measures (N = 116)*

<table>
<thead>
<tr>
<th>Unit of Analysis</th>
<th>Boundary Measures</th>
<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Mean (mi$^2$)</td>
<td>SD</td>
<td>Min. (mi$^2$)</td>
<td>Max. (mi$^2$)</td>
</tr>
<tr>
<td>Block</td>
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<td>0.10</td>
<td>--</td>
<td>0.82</td>
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<td>0.04</td>
<td>46.59</td>
</tr>
<tr>
<td>Tract</td>
<td>1.67</td>
<td>4.44</td>
<td>0.24</td>
<td>46.59</td>
</tr>
<tr>
<td>Perceptual Boundary</td>
<td>0.29</td>
<td>1.08</td>
<td>--</td>
<td>10.16</td>
</tr>
</tbody>
</table>

-- less than .005

*Structural Determinants*

The second phase of the survey involved obtaining perceptual measures of neighborhood structural determinants and endogenous variables of social disorganization.\(^5\) The questionnaire was modeled directly after the respondent questionnaire designed in the original creation of the extended model of social disorganization, in order to provide the most accurate representation of the traditional extended model of the theory of social disorganization (Sampson & Groves, 1989; Sun, Triplett & Gainey, 2004). The surveys were administered to each respondent upon completion of phase one. Participants were asked to describe conditions within the neighborhood that they previously identified to researchers in phase one of data collection, in relation to each of the variables identified in the extended model of the theory of social disorganization (Sampson & Groves, 1989).\(^6\) These variables consist of two types, the structural or exogenous variables and the intervening variables of a neighborhood. Both of these two types are comprised of a series of different variables that reflect the same indicators used in past research (See Figure 1). Table 2 presents the

---

\(^5\) See Appendix A for a copy of the complete survey.

\(^6\) See Appendix B for survey instructions, Part 2.
descriptive statistics for all of the perceptual and official structural measures and boundary files, as well as the endogenous variables.

In the current study, the structural determinants of social disorganization consist of five indicators: socioeconomic status, racial heterogeneity, residential mobility, family disruption, and urbanization. It is important to note that the operationalization of each of these variables is crafted after that used in the original implementation of contemporary models of social disorganization (Sampson & Groves, 1989). Questions related to these variables were asked in Section 6 of the respondent survey.

Perceived socioeconomic status was operationalized using four separate indicators: income, education, occupation, and home ownership. These indicators were combined to form an index of SES, with each indicator being weighted equally. Income was gathered by asking respondents, “Out of every 100 households in your neighborhood, in your opinion, how many have a household income of more than $60,000 a year?” \( M = .52, SD = .29 \). Education level was gathered using a question asking the proportion of those that are college educated \( M = .51, SD = .23 \). Occupation type was measured using a single question related to the proportion of people holding a professional or managerial position in that neighborhood \( M = .52, SD = .23 \). Finally, home ownership was measured by a question asking respondents about the proportion of those in their neighborhood that owned versus rented their home \( M = .64, SD = .58 \).

\[7 \] $60,000 was the median income of Clark County in 2010.
The perceived index of socioeconomic status ranges from .04 to .98 ($M = .54, SD = .21$), with an average level of .54 (Table 2).

Residential mobility was a single-item measure using a question related to tenure, or those who have owned their home for ten years or more. This question, question #25 of Section 6 in the survey, asked, “Out of every 100 housing units occupied in your neighborhood, in your opinion, how many house residents who have lived there for less than 10 years?” The use of housing tenure in some form as an indicator of residential mobility has been used past research and is thought to have good content validity, and so was determined to be a reasonable measure in this case (Sun, Triplett, & Gainey 2004). The perceived residential mobility ranged from .00 to 1.00 ($M = .65, SD = .32$). The average level of perceived residential mobility was .65, meaning that on average respondents believed that about two thirds of the residents in their neighborhood have lived there for less than ten years.

Racial heterogeneity was measured using several race variables combined into a Blau’s index of intergroup relations (Blau, 1977):

$$1 - \sum P_i^2$$

In the formula, $P_i$ stands for the proportion of the population (Sun, Triplett, & Gainey, 2004). The index contained six races in total, consisting of ‘White, non-Hispanic’, ‘Black, non-Hispanic’, ‘Native American, non-Hispanic’, ‘Asian/Pacific Islander, non-Hispanic’, ‘Other, non-Hispanic’, and ‘Hispanic, any race’. The perceived index of racial heterogeneity ranges from .10 to .83 ($M = .55, SD = .16$).

---

8 Questions were worded in a format that provided a number out of 100, which was then converted into a proportion. This was deemed a better alternative than asking respondents to directly identify a percentage.
Table 2

*Descriptive Statistics for Perceived Exogenous and Endogenous Factors and Official Exogenous Factors (N = 116)*

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Perceived Exogenous Factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socioeconomic Status</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>High Income</td>
<td>0.52</td>
<td>0.29</td>
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<td>1.00</td>
</tr>
<tr>
<td>Professional/Manager</td>
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<td>0.23</td>
<td>--</td>
<td>0.95</td>
</tr>
<tr>
<td>College Educated</td>
<td>0.51</td>
<td>0.24</td>
<td>--</td>
<td>0.98</td>
</tr>
<tr>
<td>Home Ownership</td>
<td>0.64</td>
<td>0.58</td>
<td>--</td>
<td>1.00</td>
</tr>
<tr>
<td>Residential Mobility</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tenure</td>
<td>0.65</td>
<td>0.32</td>
<td>--</td>
<td>1.00</td>
</tr>
<tr>
<td>Racial Heterogeneity</td>
<td>0.55</td>
<td>0.16</td>
<td>0.10</td>
<td>0.83</td>
</tr>
<tr>
<td><strong>Family Disruption</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Divorced or Separated</td>
<td>0.25</td>
<td>0.15</td>
<td>--</td>
<td>0.60</td>
</tr>
<tr>
<td>Single Parent</td>
<td>0.32</td>
<td>0.20</td>
<td>--</td>
<td>0.80</td>
</tr>
<tr>
<td>Urbanization</td>
<td>0.26</td>
<td>0.24</td>
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<td>1.00</td>
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<td><strong>Endogenous Factors</strong></td>
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<tr>
<td>Local Social Ties</td>
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<td>0.71</td>
<td>0.40</td>
<td>3.60</td>
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<tr>
<td>Unsupervised Peer Groups</td>
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<td>0.77</td>
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<td>Organizational Participation</td>
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<td>--</td>
<td>2.00</td>
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<tr>
<td><strong>Official Exogenous Factors</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socioeconomic Status</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Income</td>
<td>0.55</td>
<td>0.20</td>
<td>0.10</td>
<td>0.97</td>
</tr>
<tr>
<td>Professional/Manager</td>
<td>0.12</td>
<td>0.06</td>
<td>--</td>
<td>0.36</td>
</tr>
<tr>
<td>College Educated</td>
<td>0.61</td>
<td>0.16</td>
<td>0.12</td>
<td>0.90</td>
</tr>
<tr>
<td>Home Ownership</td>
<td>0.62</td>
<td>0.24</td>
<td>--</td>
<td>1.00</td>
</tr>
<tr>
<td>Residential Mobility</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tenure</td>
<td>0.78</td>
<td>0.18</td>
<td>0.33</td>
<td>1.00</td>
</tr>
<tr>
<td>Racial Heterogeneity</td>
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<td>0.15</td>
<td>--</td>
<td>0.59</td>
</tr>
<tr>
<td><strong>Family Disruption</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Divorced or Separated</td>
<td>0.15</td>
<td>0.07</td>
<td>0.03</td>
<td>0.40</td>
</tr>
<tr>
<td>Single Parent</td>
<td>0.28</td>
<td>0.15</td>
<td>--</td>
<td>0.79</td>
</tr>
<tr>
<td>Urbanization</td>
<td>1.00</td>
<td>--</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

-- Less than .005.

9 The next section will provide descriptive details of how official data was collected. However, all measures are provided here for comparative purposes.
Family disruption was measured using two indicators: a question representing the percentage of divorced families and a question representing the percentage of single parent family residences. Using these two indicators as a proper measure of the variable of family disruption was also common in past literature (Sampson & Groves, 1989; Sun, Triplett, & Gainey 2004). The level of divorced or separated families ranged from .00 to .60 ($M = .25, SD = .15$). The level of single parent families ranged from .00 to .80 ($M = .32, SD = .20$). These indicators were combined to create an index for family disruption, in which both indicators were given equal weight. The perceived percentage of family disruption in the sample ranged from .05 to .63. The average level of family disruption was .28, meaning that in general respondents believed that the majority of families in their neighborhood contained a married, two parent structure.

* Collective Efficacy

Neighborhood endogenous variables, or those related to collective efficacy, were gathered solely with the respondent survey and were used to comprise the endogenous characteristics in both the official and perceptual models. Indicators of collective efficacy include measures of local social ties, unsupervised teenage peer groups, and organizational participation. The four remaining parts of the respondent survey (Sections 1, 3 and 5) presented questions pertaining to the endogenous variables of social disorganization theory as identified in the contemporary models. Questions were modeled after those used in past research to measure collective efficacy, with some questions being added related to organizational participation (Sampson, Raudenbush, & Earls, 1997; Sampson & Groves, 1989).
The measures of local social ties, control over unsupervised teenage peer groups, and organizational participation, were designed to reflect the underlying dimensions of collective efficacy. Factor analysis was conducted on 13 related items of the survey to assess their factorability.\textsuperscript{10} Three Eigen values greater than 1 were observed, identifying that the majority of the variation in the relationship was explained by three concepts. This confirmed the use of three separate endogenous variables. The first Eigen value showed the local social ties factor explained 34\% of the variance, the control over unsupervised teenage peer groups factor explained 15\% of the variance, and the organizational participation factor explained 8\% of the variance. Strengths of the correlations between the items measuring local social ties ranged from .34 to .64 ($p < .01$), while items measuring control over unsupervised teenage peer groups ranged between .54 and .55 ($p < .01$), which both indicate moderate factorability. Strengths of the correlations between items measuring organizational participation were weaker – ranging between .22 and .41 – but were statistically significant ($p <.01$). The Kaiser-Meyer-Olkin measure of sampling adequacy was .84, above the recommended value of .6; and Barlett’s test of sphericity was significant ($\chi^2 = 457.029$, $p < .01$).

A neighborhood’s local social ties, or a measure of the collective social cohesion and friendships shared, was assessed with five questions centered around the respondent’s relationship with their neighbors and their interaction and trust with one another. For example, four of the questions asked how strongly the respondents agreed with the following statements: “Mine is a close knit neighborhood”, “People in my

\textsuperscript{10} All of the questions were used except for question 4, a question on voter participation, due to the low relationship it showed to all other variables.
neighborhood are willing to help their neighbors”, “People in my neighborhood can be trusted”, and “People in my neighborhood do not share the same values”. The last question asked respondents how likely it would be for neighbors to organize together in order to save a fire station closing due to budgetary constraints. All five questions were then used to form a five-item Likert scale (scored 0-4), representing one measure of the neighborhoods local social ties. The level of perceived local social ties in the sample ranged from 1.60 to 3.40, with a mean of 2.1, indicating that strong social ties existed in their neighborhoods.

The neighborhood’s level of control over unsupervised teenage peer groups, or the amount of social control within the area, was measured using a four-item Likert scale. Respondents were asked how likely it would be for them or their neighbors to intervene in the following four situations, “If a group of neighborhood children were skipping school and hanging out on a street corner...”, “If some children were spray painting graffiti on a local building...”, “If a child was showing disrespect to an adult...”, and “If there was a fight in front of your house and someone was being beaten up...”. In each of the questions, respondents chose between five options, “(0) Very unlikely, (1) Unlikely, (2) Neither unlikely nor likely, (3) Likely, and (4) Very likely”. The level of control over teenage peer groups in the sample ranged from .25 to 4.00, with an average level of 2.4. This means that on average, respondents believed that their neighbors were somewhat likely to demonstrate social control over unsupervised teens.

Organizational participation, or a respondent’s level of involvement in organizations and community events in the local community, was gauged using three questions related to community involvement. All three of the questions were indexed to
form a single measure of organizational participation. The organizational participation in the sample varied from .00 to 1.67, with a mean of .21, indicating that neighborhood organizational participation in the sample was quite low. The majority neighbors are unlikely to have recently participated in community organization of any kind.

Official Measures

**Boundary**

Administrative boundary files were developed from 2010 TIGER files available online through the U.S. Census Bureau’s website.\(^\text{11}\) Three files corresponding to the tracts, block groups, and blocks within Clark County, Nevada were created. The sample consists of 2,074 shared or unique blocks, 238 shared or unique block groups, and 168 shared or unique tracts. Blocks within the sample ranged from 0.00263mi\(^2\) to 0.82mi\(^2\), with the average size block being 0.06mi\(^2\). Block groups ranged from 0.04mi\(^2\) to 46.59mi\(^2\), with the average size block group being 1.04mi\(^2\). Finally, tracts ranged from 0.24mi\(^2\) to 46.59mi\(^2\), with the average size tract being 1.67mi\(^2\) (See Table 1).

**Neighborhood Condition**

Official measures of neighborhood conditions were obtained from the Census Bureau’s American Communities Survey (ACS).\(^\text{12}\) Many of the indicators used mirrored those found in the perceptual survey, with similar questions being asked in the ACS. For example, the index of socioeconomic status was created using four questions centered around respondent’s income level, occupation type, education level, and whether or not


\(^{12}\) The ACS was begun by the U.S. Census as a method for collecting housing and demographic data every year, rather than every ten years as with the normal census long form survey. The ACS collects data from over three million homes each year, and also creates a five-year estimate file comparing states nationwide.
they owned their homes. The official index of socioeconomic status ranged from .12 to .79 ($M = .47, SD = .13$). The racial heterogeneity index ranged from .00 to .59 ($M = .29, SD = .15$). Residential mobility ranged from .33 to 1.00 ($M = .78, SD = .18$). The familial stability index in the sample ranged from .02 to .54 ($M = .28, SD = .10$). Finally, it is important to note that the official level of urbanization was a constant 1.00, due to the population density of the Las Vegas valley and the manner in which the U.S. Census measures urban environments. Due to this lack of variation, urbanization was removed as a variable because comparisons between perceptual data and the official data would have been inconclusive.

**Crime Rates**

Finally, 2010 crime data for Clark County, Nevada were obtained from the Las Vegas Metropolitan Police Department. The Las Vegas valley is the highest population area in the county. The data used consists of calls for service data for the year 2010.

Three crime categories serve as the dependent variables in the path models and include the violent (i.e., robbery and assault), property (i.e., burglary, larceny, and motor vehicle theft), and a total crime rate for Las Vegas in 2010. It is important to note that homicide and rape crimes were not included in the violent crime rate. This was done for several reasons. Their rare occurrence, their classification as “passion crimes”, and the fact that they are not traditionally considered street level incidents, were all factors in the decision. Each rate was created by dividing the total crime count associated with each
crime category by the corresponding block group’s population, and multiplying the result by 1,000. Crime rates are based on calls for service.\textsuperscript{13}

Table 3 presents the descriptive statistics for the crime counts for the sample. Violent crimes in the block groups within our study area ranged from 0 to 411 incidents, with the average number of violent crime incidents per block group being 19.14 ($M = 19.14$, $SD = 45.18$). Property crimes ranged from 6 to 759 incidents, with the average number of property crimes being 57.59 ($M = 57.59$, $SD = 100.32$). Lastly, the total crime within our sample ranged from 6 incidents to 1,206, with a mean of 77.09 ($M = 77.09$, $SD = 143.63$).

Crime rate descriptives are also presented in Table 3. For example, the violent crime rate for the block groups in our sample ranged from 0.00 to 637.21, with the average violent crime rate being 16.54 ($M = 16.54$, $SD = 67.28$). This means that on average, block groups within the sample had more than 16 violent crime incidents per 1,000 residents in the year 2010. The property crime rate ranged from 1.04 to 1232.56 ($M = 47.29$, $SD = 138.54$), with a mean rate of 47.29. Finally, the total crime rate ranged from 1.73 to 1869.77 ($M = 63.83$, $SD = 204.51$), with an average total crime rate of 63.83 per 1,000 residents.

The 2010 calls for service data was geocoded using the 10.0 North American Geocode service address locator provided within ArcGIS 10. Each individual crime type

\textsuperscript{13} Disorder variables (vandalism, graffiti, drug offenses, solicitation, etc.) were considered, but ultimately excluded. Vandalism, for example, was considered because of its use as a proxy for delinquency (Sampson & Groves, 1989). However, many of these variables were captured within the data under a catch-all labeled “other disturbance” which made distinguishing certain types of disorder problematic.
Table 3

*Descriptive Statistics for Crime Counts and Rates at the Block Group*\(^{14}\) Level (n = 93)

<table>
<thead>
<tr>
<th>Block Group</th>
<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Calls for Service</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Crime</td>
<td>77.09</td>
<td>143.64</td>
<td>6.00</td>
<td>1,206.00</td>
</tr>
<tr>
<td>Violent Crime</td>
<td>19.14</td>
<td>45.18</td>
<td>--</td>
<td>411.00</td>
</tr>
<tr>
<td>Property Crime</td>
<td>57.95</td>
<td>100.32</td>
<td>6.00</td>
<td>795.00</td>
</tr>
<tr>
<td>Crime Rate (per 1,000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Crime</td>
<td>63.83</td>
<td>204.51</td>
<td>1.73</td>
<td>1,869.77</td>
</tr>
<tr>
<td>Violent Crime</td>
<td>16.54</td>
<td>67.28</td>
<td>--</td>
<td>637.21</td>
</tr>
<tr>
<td>Property Crime</td>
<td>47.29</td>
<td>138.54</td>
<td>1.04</td>
<td>1,232.56</td>
</tr>
<tr>
<td>Population</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1,976</td>
<td>1,277</td>
<td>521</td>
<td>7,699</td>
</tr>
</tbody>
</table>

-- Less than .005

data set was cleaned, with inaccurate address matches being removed to improve overall accuracy. Of the 48,728 property crimes, 45,896 were matched to a street address or home address (94%), 80% of the violent crimes accurately geocoded and 90% of all crimes were accurately geocoded (90%). For the analysis that follows, crime data were aggregated to the block group level.

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\(^{14}\) The block group level was identified as the best overall indicator of perceptual neighborhood boundary, in terms of both count and area. See Chapter 5: Results, Research Hypothesis 1 for further discussion.
CHAPTER 4

ANALYTIC APPROACHES

In order to test the current hypotheses, three unique analytic methods were required. In brief, the three hypotheses were that official measures of neighborhood boundary are inconsistent with perceptual boundaries, official measures of structural condition that characterize social disorganization are dissimilar to corresponding perceptual measures, and lastly, that perceptual models of social disorganization outperform traditional models. The following section presents the details related to the testing of each of these research hypotheses.

Testing Research Hypothesis I

The first hypothesis of this study states that official census boundaries of neighborhood (measured at the block, block group, and tract level) are inconsistent with the perceptual boundaries of neighborhood, both in terms of the number of each geographic unit and in terms of the area that each unit compromises. To test this hypothesis, the perceived neighborhood boundary shapefiles from the first phase of the respondent survey were spatially overlaid with a 2010 U.S. Census Bureau TIGER shapefile for Clark County, Nevada, which contains each respective official boundary (tracts, block groups, and blocks). Individual respondents’ perceived boundary shapefiles were then compared to the census-defined data in two differing ways.

First, the total number of “neighborhoods”, measured at each of the three census defined data levels (tract, block group, and block), were determined based on visual inspection of data (see Figure 1) compared to each respondents’ perceived boundary shapefile. Complete concordance between perceived and official neighborhoods would
reflect a single block, block group, or tract associated with a respondents’ perceived neighborhood. A one-sampled t test was used to assess the first research hypothesis and aid in determining which official proxy should be used to test the third hypothesis.

Second, respondents’ perceived boundary shapefiles were compared directly to the census defined boundaries in terms of area. The total extracted area (mi$^2$) of the respondent’s boundary file was divided by the entire area (mi$^2$) of all census defined data in which the respondent’s home address was contained (i.e. tract, block group, and block). Complete concordance between the official and perceived areas that comprise a respondent’s neighborhood would result in a value of 1, with lower scores reflecting that respondent’s neighborhood boundaries were smaller in size to comparable official boundaries, and higher scores indicating that respondent boundaries were larger than official boundaries. From this, the proportion of the amount that each respondent’s perceived neighborhood that was contained by the corresponding census defined boundaries was determined (see Table 2). Paired sample t tests were used to test whether perceived neighborhood boundaries were statistically different from census-defined boundaries in terms of area.

It is important to note that a single block group or tract is often used as an indicator of neighborhood when conducting social disorganization research, and therefore it is largely assumed that a person believes their neighborhood is as large as that particular block group or tract. For this reason, the results from both data analysis methods will be combined in order to determine which level is most effective at containing a respondent’s perceived neighborhood boundary, as well as the proportion that it makes up. While it might be possible that a single tract or block group
encompasses most of the perceived boundaries provided by a respondent, the particular perceived boundary might only comprise a small portion of its corresponding tract or block group. This would therefore mean that the respondents’ perceived neighborhood is being captured by the census-defined data, but that other neighborhoods are also being captured and grouped along with it.

Testing Research Hypothesis II

The second hypothesis states that each of the official measures of neighborhood structural condition that characterizes social disorganization is dissimilar to corresponding perceptual measures. To test this hypothesis, comparisons between perceptual indicators of social disorganization and official indicators of those same measures were made. Specifically, paired sample t tests were used to compare the means of perceived exogenous variables to the corresponding variables contained in official data. Results provide insight into the accuracy of official data compared to respondents’ perceptions of neighborhood structural determinants to crime.

Testing Research Hypothesis III

The third hypothesis states that perceptual models of social disorganization outperform traditional models in terms of their ability to explain variation in levels of crime. This assessment involves using data from each previous stage to determine which measure is a better reflection of a neighborhood’s social organization in the form of existing crime: the respondents’ perceptions or official data. The exogenous structural variables and the endogenous intervening variables will serve as the independent variables in this section. The 2010 calls for service crime rates from the city of Las
Vegas will serve as the dependent variable. A comparison of $R^2$ values will be made using path model analysis.

Path models of the extended model of the theory of social disorganization used by previous researchers (see Figure 3) will be estimated using the 2010 Las Vegas crime data and both the perceived and official neighborhood characteristics data (Sampson & Groves, 1989; Sun, Triplet, & Gainey, 2004; Veysey & Messner, 1999). In total, six different models will be run, one for each crime rate matched to either perceived or official neighborhood characteristics (violent crime rate, property crime rate, and total crime rate). For both the perceptual and official models, the intervening variables collected from survey data will remain the same. As can be referenced in Figure 3, each model accounts for every possible relationship between the four included structural variables, the three intervening variables, and each of the crime rates. The results from this analysis will allow us to determine which dataset better reflects the variation present in the relationship between the independent variables and crime within the Las Vegas valley.
Figure 3. An illustration of the social disorganization path models used in the current analysis.
CHAPTER 5

RESULTS

Research Hypothesis I

Research hypothesis I states that official census boundaries of neighborhood (measured at the block, block group, and tract level) are inconsistent with the perceptual boundaries of neighborhood, in terms of the number of each geographic unit and in terms of the area that each unit compromises. Table 4 presents a summary of the number of each geographic unit contained within the respondents boundary file. It outlines, by numerical count, the blocks, block groups, and tracts, contained within respondent’s boundary files. It also presents the percentage and cumulative percentage of each count within the sample. Findings show that perceptual neighborhood boundaries vastly differ from administratively defined boundaries. Therefore, we reject the null hypothesis that official census boundaries are consistent with perceptual boundaries in favor of the alternative hypothesis.

Overall, only 10.3% of respondents identified that their neighborhood boundary contained a single census block. In other words, almost all (89.7%) of respondents’ perceived neighborhoods contained multiple blocks. In fact, the majority of respondent’s files (58.9%) contained 5 or more blocks.

Conversely, a clear majority of respondents’ perceived neighborhood (68.1%) contained only a single block group, with a little more than 6% of perceived neighborhoods containing five or more block groups.

Finally, four out of five perceived boundaries contained a single census tract, with less than 3% containing 5 or more tract files. These results seem valid in terms of
Table 4

*Blocks, Block Groups, and Tracts Contained within Respondent Perceived Neighborhood Boundaries (N = 116)*

<table>
<thead>
<tr>
<th>Census Areas</th>
<th>Number</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Blocks</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>12</td>
<td>10.3</td>
<td>10.3</td>
</tr>
<tr>
<td>2</td>
<td>11</td>
<td>9.5</td>
<td>19.8</td>
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<td>3</td>
<td>14</td>
<td>12.1</td>
<td>31.9</td>
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<tr>
<td>4</td>
<td>11</td>
<td>9.5</td>
<td>41.4</td>
</tr>
<tr>
<td>5 or more</td>
<td>68</td>
<td>58.9</td>
<td>100.0</td>
</tr>
<tr>
<td><strong>Block Groups</strong></td>
<td></td>
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</tr>
<tr>
<td>1</td>
<td>79</td>
<td>68.1</td>
<td>68.1</td>
</tr>
<tr>
<td>2</td>
<td>19</td>
<td>16.4</td>
<td>84.5</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
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<tr>
<td>4</td>
<td>3</td>
<td>2.6</td>
<td>94.0</td>
</tr>
<tr>
<td>5 or more</td>
<td>7</td>
<td>6.0</td>
<td>100.0</td>
</tr>
<tr>
<td><strong>Tracts</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>96</td>
<td>82.8</td>
<td>82.8</td>
</tr>
<tr>
<td>2</td>
<td>12</td>
<td>10.3</td>
<td>93.1</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>3.4</td>
<td>96.6</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0.9</td>
<td>97.4</td>
</tr>
<tr>
<td>5 or more</td>
<td>3</td>
<td>2.6</td>
<td>100.0</td>
</tr>
</tbody>
</table>

geographical area, since the census tract is on average much larger than either block groups, or blocks.

Findings presented in Table 5 indicate that the size of perceptual neighborhood boundaries is largely dissimilar to the size of official neighborhood boundaries. For example, the average respondent identified that their neighborhood boundary was 8.6 times larger than their respective census block in terms of squared miles. Conversely, the average perceived neighborhood encompasses 74% of the total area of the block group in which it falls, and a little less than 30% of the total area of its corresponding tract.
Table 5

*Proportion of Respondents’ Perceived Neighborhood Contained by the Census Block, Block Group, and Tract in which They Live (N = 116)*

<table>
<thead>
<tr>
<th>Census Areas</th>
<th>Mean (mi²)</th>
<th>SD</th>
<th>Min. (mi²)</th>
<th>Max. (mi²)</th>
<th>Median (mi²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blocks</td>
<td>8.55</td>
<td>12.34</td>
<td>.08</td>
<td>60.11</td>
<td>3.30</td>
</tr>
<tr>
<td>Block Groups</td>
<td>0.74</td>
<td>1.78</td>
<td>--</td>
<td>15.59</td>
<td>0.22</td>
</tr>
<tr>
<td>Tracts</td>
<td>0.29</td>
<td>0.81</td>
<td>--</td>
<td>7.74</td>
<td>0.08</td>
</tr>
</tbody>
</table>

-- Less than 0.005

For statistical comparison, *t* tests were computed on both area and count data. Table 6 presents the findings from both *t* tests. In terms of count, a one-sample *t* test was computed using both perceptual and official boundary data and a test value of 1.15

Results reveal that blocks significantly differ from perceptual data in terms of count, *t*(115) = 2.64, *p* = .01. Said differently, multiple blocks are needed to reflect a single perceptual boundary. Block groups are also significantly different from perceptual data, *t*(115) = 2.98, *p* = .00; again indicating that multiple block groups are needed to reflect a single perceptual boundary of one’s neighborhood. Finally, tracts are shown to be significantly different from perceptual data in terms of count, *t*(115) = 2.65, *p* = .01.

Based solely on counts, none of the official boundary measures of neighborhood accurately reflects perceptual boundaries.

In order to determine whether perceptual boundary areas of neighborhood differ from official boundary areas, a paired-sample *t* test was conducted using both the respondent identified boundary data and official boundary data for the block, block group, and tract levels.

15 Each respondent lives in a single neighborhood, therefore, the test value used to compare official neighborhood is 1.
Table 6

*Results of T-Tests Comparing Perceived and Official Boundary Measures (N = 116)*

<table>
<thead>
<tr>
<th>Boundary</th>
<th>Perceived</th>
<th>Official</th>
<th>( t )</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>One Sample ( t )-test (Test Value = 1))</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block</td>
<td>1</td>
<td>17.88</td>
<td>2.637*</td>
<td>115</td>
</tr>
<tr>
<td>Block Group</td>
<td>1</td>
<td>2.05</td>
<td>2.982*</td>
<td>115</td>
</tr>
<tr>
<td>Tract</td>
<td>1</td>
<td>1.45</td>
<td>2.647*</td>
<td>115</td>
</tr>
<tr>
<td><strong>Paired Sample ( t )-test)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Area</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block</td>
<td>0.286</td>
<td>0.055</td>
<td>2.317*</td>
<td>115</td>
</tr>
<tr>
<td>Block Group</td>
<td>0.286</td>
<td>1.038</td>
<td>-1.800</td>
<td>115</td>
</tr>
<tr>
<td>Tract</td>
<td>0.286</td>
<td>1.669</td>
<td>-3.275*</td>
<td>115</td>
</tr>
</tbody>
</table>

*Note:* \( *p < .05 \)

Comparisons at the block level confirm that the average size of the perceptual boundary (0.286mi\(^2\)) differs significantly from that of the average size of a census block, \( t(115) = 2.32, p = .022 \). This reveals that blocks are, on average, too small to be a valid approximation of neighborhood. Conversely, the block group \( t \)-test reveals that the average area of the perceptual boundary does not significantly differ from that of the average size block group, \( t(115) = -0.18, p = .074 \), indicating that the block group level is perhaps a good proxy for neighborhood size. Finally, the tract level \( t \)-test reveals that the average area of the perceptual boundary does significantly differ from that of the average tract, \( t(115) = -3.28, p = .00 \). This reveals that the tract level is too large to properly reflect neighborhood boundary.

Comparison of the count and area data and corresponding \( t \)-tests reveals that of the three official proxies of neighborhood, the block group level represents a better indicator than either blocks or tracts. First, nearly 70% of all perceptual boundaries were
contained within a single block group and the average perceived boundary comprised 74% of the total area of its respective block group. These two results reveal that perceptual neighborhood boundary files are most likely to contain the largest proportion of but not exceed the size of the average block group. Furthermore, t-tests show that while block groups differ significantly from perceptual boundaries in terms of count, they are closer to significance than census blocks. Finally, block groups were the only official proxy measure that was not significantly different from perceptual boundaries in terms of area. So, while not an exact match, block group boundaries are at least similar to perceptual boundaries in respect to their overall area in square miles.

Research Hypothesis II

The study’s second research hypothesis states that each of the official measures of neighborhood structural condition that characterizes social disorganization is dissimilar to corresponding perceptual measures. The null hypothesis that official measures of neighborhood structural condition are similar to perceptual measures is rejected, in favor of the alternative hypothesis. Table 7 shows the results of each paired t test comparing the mean official and perceptual measures of neighborhood structural condition.

Findings show that all but two perceived structural measures of social disorganization theory differ significantly (p < .05) from their official counterparts. On average, sample respondents overestimated the percentage of those in their neighborhood holding professional or managerial positions by more than 40%. They underestimated the percentage of those that were college educated by just under 10%. The percentage of those owning their home was underestimated by a little over 14% by respondents. Racial heterogeneity was overestimated by nearly 26%. Lastly, the percentage of divorced or
Table 7

Results of T-Tests Comparing Official and Perceptual Measures of Neighborhood Structural Condition (N = 116)

<table>
<thead>
<tr>
<th>Exogenous Variables</th>
<th>Mean Diff.</th>
<th>SD</th>
<th>t</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SES</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Income</td>
<td>0.03</td>
<td>0.26</td>
<td>1.14</td>
<td>.256</td>
</tr>
<tr>
<td>Professional/Managerial</td>
<td>-0.40</td>
<td>0.23</td>
<td>-18.81</td>
<td>.000*</td>
</tr>
<tr>
<td>College Educated</td>
<td>0.10</td>
<td>0.23</td>
<td>4.57</td>
<td>.000*</td>
</tr>
<tr>
<td>Home Ownership</td>
<td>-0.02</td>
<td>0.60</td>
<td>-0.35</td>
<td>.730</td>
</tr>
<tr>
<td>Residential Mobility</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tenure</td>
<td>0.14</td>
<td>0.31</td>
<td>5.04</td>
<td>.000*</td>
</tr>
<tr>
<td>Racial Heterogeneity</td>
<td>-0.26</td>
<td>0.20</td>
<td>13.51</td>
<td>.000*</td>
</tr>
<tr>
<td>Family Disruption</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Divorced/Separated</td>
<td>-0.09</td>
<td>0.16</td>
<td>-6.19</td>
<td>.000*</td>
</tr>
<tr>
<td>Single Parent</td>
<td>-0.04</td>
<td>0.23</td>
<td>-1.77</td>
<td>.080*</td>
</tr>
<tr>
<td>Urbanization</td>
<td>0.74</td>
<td>0.24</td>
<td>32.70</td>
<td>.000*</td>
</tr>
</tbody>
</table>

*p < .05

separated families was overestimated by 9%. Results indicate that overall official measures of neighborhood condition are a poor representation of resident perceptions of structural determinants.

Research Hypothesis III

Hypothesis III of the study states that perceptual models of social disorganization outperform traditional models in terms of their ability to explain variation in levels of crime and disorder. Results of path analysis for six models, three official and three perceptual, are presented in Tables 8-13, looking at three crime types. None of the explained variances in the perceived models exceeds the official models; therefore, we
fail to reject the null hypothesis in favor of the alternative that states that perceptual models will outperform official models.

Results of Path Model 1 are presented in Table 8. Findings show the direct and indirect effects of endogenous and exogenous data, based on official structural determinants data, as well as the zero-order correlation and the overall explained variance of the crime model, which accounted for 27% of the variation in the total crime rate. Socioeconomic status and residential mobility shared direct significant relationships with the total crime rate. Socioeconomic status had a negative (-.35) significant relationship \((p < .10)\) with the total crime rate, implying that as the official socioeconomic status of a neighborhood goes up, the total crime rate goes down. Meanwhile, residential mobility had a significant \((p < .05)\) negative relationship (.24) with the total crime rate, implying that as residential mobility goes up, the total crime rate drops.

Results of Path Model 2 are presented in Table 9. Findings show the direct and indirect effects of endogenous and exogenous data, based on official structural determinants data, as well as the zero-order correlation and the overall explained variance of the crime model, which accounted for 33% of the variation in the violent crime rate. Socioeconomic status, residential mobility, family disruption, local friendship networks, and peer group affiliation all shared significant relationships with the dependent variable (violent crime rate). Socioeconomic status shared a significant \((p < .05)\) negative relationship (-.47) with the violent crime rate. Residential mobility shared a significant \((p < .05)\) negative relationship (-.22) with the violent crime rate. Family disruption shared a significant \((p < .10)\) positive relationship (.20). Local friendship networks
Table 8

*Indirect, Direct, Total Effects and Zero-Order Correlations of Variables Predicting Total Crime - Official (Path Model 1)*

<table>
<thead>
<tr>
<th>Concepts/variables</th>
<th>Direct effect</th>
<th>Total indirect effects</th>
<th>Total effect</th>
<th>Zero-order correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neighborhood structural determinants</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-economic status</td>
<td>-0.350*</td>
<td>0.010</td>
<td>-0.340</td>
<td>-0.381*</td>
</tr>
<tr>
<td>Racial heterogeneity</td>
<td>-0.097</td>
<td>0.000</td>
<td>-0.097</td>
<td>-0.017</td>
</tr>
<tr>
<td>Residential mobility</td>
<td>-0.264**</td>
<td>0.000</td>
<td>-0.264</td>
<td>-0.122</td>
</tr>
<tr>
<td>Family Disruption</td>
<td>0.244</td>
<td>0.000</td>
<td>0.244</td>
<td>0.324*</td>
</tr>
<tr>
<td><strong>Endogenous community characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local friendship networks</td>
<td>0.216</td>
<td>--</td>
<td>0.216</td>
<td>-0.053</td>
</tr>
<tr>
<td>Peer group affiliation</td>
<td>-0.246</td>
<td>--</td>
<td>-0.246</td>
<td>-0.128</td>
</tr>
<tr>
<td>Organizational participation</td>
<td>0.077</td>
<td>--</td>
<td>0.077</td>
<td>0.072</td>
</tr>
</tbody>
</table>

*Note:* Due to the skewed nature of the dependent variable, a log-normal transformation was applied to the dependent variable.

$R^2=0.27$

-- Indicates no indirect path.

*p < .10; **p < .05
Table 9

*Indirect, Direct, Total Effects and Zero-Order Correlations of Variables Predicting Violent Crime - Official (Path Model 2)*

<table>
<thead>
<tr>
<th>Concepts/variables</th>
<th>Direct effect</th>
<th>Total indirect effects</th>
<th>Total effect</th>
<th>Zero-order correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neighborhood structural determinants</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-economic status</td>
<td>-0.476**</td>
<td>0.010</td>
<td>-0.466</td>
<td>-0.481*</td>
</tr>
<tr>
<td>Racial heterogeneity</td>
<td>-0.097</td>
<td>0.000</td>
<td>-0.097</td>
<td>0.036</td>
</tr>
<tr>
<td>Residential mobility</td>
<td>-0.225**</td>
<td>0.000</td>
<td>-0.225</td>
<td>-0.077</td>
</tr>
<tr>
<td>Family Disruption</td>
<td>0.198*</td>
<td>0.000</td>
<td>0.198</td>
<td>0.364*</td>
</tr>
<tr>
<td><strong>Endogenous community characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local friendship networks</td>
<td>0.229*</td>
<td>--</td>
<td>0.229</td>
<td>-0.042</td>
</tr>
<tr>
<td>Peer group affiliation</td>
<td>-0.224*</td>
<td>--</td>
<td>-0.224</td>
<td>-0.115</td>
</tr>
<tr>
<td>Organizational participation</td>
<td>0.085</td>
<td>--</td>
<td>0.085</td>
<td>0.042</td>
</tr>
</tbody>
</table>

Note: Due to the skewed nature of the dependent variable, a log-normal transformation was applied to the dependent variable.

$R^2=0.33$

-- Indicates no indirect path.

*p < .10; **p < .05
Table 10

*Indirect, Direct, Total Effects and Zero-Order Correlations of Variables Predicting Property Crime - Official (Path Model 3)*

<table>
<thead>
<tr>
<th>Concepts/variables</th>
<th>Direct effect</th>
<th>Total indirect effects</th>
<th>Total effect</th>
<th>Zero-order correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neighborhood structural determinants</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-economic status</td>
<td>-0.270**</td>
<td>0.010</td>
<td>-0.260</td>
<td>-0.319*</td>
</tr>
<tr>
<td>Racial heterogeneity</td>
<td>-0.080</td>
<td>0.000</td>
<td>-0.080</td>
<td>-0.020</td>
</tr>
<tr>
<td>Residential mobility</td>
<td>-0.268**</td>
<td>0.000</td>
<td>-0.268</td>
<td>-0.134</td>
</tr>
<tr>
<td>Family Disruption</td>
<td>0.264**</td>
<td>0.000</td>
<td>0.264</td>
<td>0.305*</td>
</tr>
<tr>
<td><strong>Endogenous community characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local friendship networks</td>
<td>0.201</td>
<td>--</td>
<td>0.201</td>
<td>-0.048</td>
</tr>
<tr>
<td>Peer group affiliation</td>
<td>-0.238*</td>
<td>--</td>
<td>-0.238</td>
<td>-0.117</td>
</tr>
<tr>
<td>Organizational participation</td>
<td>0.069</td>
<td>--</td>
<td>0.069</td>
<td>0.076</td>
</tr>
</tbody>
</table>

*Note:* Due to the skewed nature of the dependent variable, a log-normal transformation was applied to the dependent variable.

$R^2=0.23$

-- Indicates no indirect path.

*p < .10; **p < .05
Table 11

*Indirect, Direct, Total Effects and Zero-Order Correlations of Variables Predicting Total Crime - Perceived* (Path Model 4)

<table>
<thead>
<tr>
<th>Concepts/variables</th>
<th>Direct effect</th>
<th>Total indirect effects</th>
<th>Total effect</th>
<th>Zero-order correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neighborhood structural determinants</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-economic status</td>
<td>-0.186</td>
<td>0.030</td>
<td>-0.156</td>
<td>-0.189</td>
</tr>
<tr>
<td>Racial heterogeneity</td>
<td>0.050</td>
<td>0.000</td>
<td>0.050</td>
<td>0.128</td>
</tr>
<tr>
<td>Residential mobility</td>
<td>-0.276*</td>
<td>0.000</td>
<td>-0.276</td>
<td>-0.253*</td>
</tr>
<tr>
<td>Family Disruption</td>
<td>0.018</td>
<td>0.000</td>
<td>0.018</td>
<td>0.065</td>
</tr>
<tr>
<td><strong>Endogenous community characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local friendship networks</td>
<td>0.135</td>
<td>--</td>
<td>0.135</td>
<td>-0.053</td>
</tr>
<tr>
<td>Peer group affiliation</td>
<td>-0.200</td>
<td>--</td>
<td>-0.200</td>
<td>-0.128</td>
</tr>
<tr>
<td>Organizational participation</td>
<td>0.132</td>
<td>--</td>
<td>0.132</td>
<td>0.072</td>
</tr>
</tbody>
</table>

*Note:* Due to the skewed nature of the dependent variable, a log-normal transformation was applied to the dependent variable.

$R^2=0.14$

-- Indicates no indirect path.

*p < .10
Table 12

*Indirect, Direct, Total effects and Zero-Order Correlations of Variables Predicting Violent Crime - Perceived (Path Model 5)*

<table>
<thead>
<tr>
<th>Concepts/variables</th>
<th>Direct effect</th>
<th>Total indirect effects</th>
<th>Total effect</th>
<th>Zero-order correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neighborhood structural determinants</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-economic status</td>
<td>-0.253*</td>
<td>0.030</td>
<td>-0.223</td>
<td>-0.235*</td>
</tr>
<tr>
<td>Racial heterogeneity</td>
<td>0.030</td>
<td>0.000</td>
<td>0.030</td>
<td>0.135</td>
</tr>
<tr>
<td>Residential mobility</td>
<td>-0.336*</td>
<td>0.000</td>
<td>-0.336</td>
<td>-0.312*</td>
</tr>
<tr>
<td>Family Disruption</td>
<td>0.087</td>
<td>0.000</td>
<td>0.087</td>
<td>0.149</td>
</tr>
<tr>
<td><strong>Endogenous community characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local friendship networks</td>
<td>0.163</td>
<td>--</td>
<td>0.163</td>
<td>-0.042</td>
</tr>
<tr>
<td>Peer group affiliation</td>
<td>-0.182</td>
<td>--</td>
<td>-0.182</td>
<td>-0.115</td>
</tr>
<tr>
<td>Organizational participation</td>
<td>0.124</td>
<td>--</td>
<td>0.124</td>
<td>0.042</td>
</tr>
</tbody>
</table>

*Note:* Due to the skewed nature of the dependent variable, a log-normal transformation was applied to the dependent variable.

$R^2=0.20$

-- Indicates no indirect path.

*p < .10
Table 13

*Indirect, Direct, Total Effects and Zero-Order Correlations of Variables Predicting Property Crime - Perceived (Path Model 6)*

<table>
<thead>
<tr>
<th>Concepts/variables</th>
<th>Direct effect</th>
<th>Total indirect effects</th>
<th>Total effect</th>
<th>Zero-order correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neighborhood structural determinants</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-economic status</td>
<td>-0.165</td>
<td>0.030</td>
<td>-0.135</td>
<td>-0.166</td>
</tr>
<tr>
<td>Racial heterogeneity</td>
<td>0.049</td>
<td>0.000</td>
<td>0.049</td>
<td>0.114</td>
</tr>
<tr>
<td>Residential mobility</td>
<td>-0.238*</td>
<td>0.000</td>
<td>-0.238</td>
<td>-0.217*</td>
</tr>
<tr>
<td>Family Disruption</td>
<td>-0.007</td>
<td>0.000</td>
<td>-0.007</td>
<td>0.036</td>
</tr>
<tr>
<td><strong>Endogenous community characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local friendship networks</td>
<td>0.118</td>
<td>--</td>
<td>0.118</td>
<td>-0.048</td>
</tr>
<tr>
<td>Peer group affiliation</td>
<td>-0.184</td>
<td>--</td>
<td>-0.184</td>
<td>-0.117</td>
</tr>
<tr>
<td>Organizational participation</td>
<td>0.129</td>
<td>--</td>
<td>0.129</td>
<td>0.076</td>
</tr>
</tbody>
</table>

*Note:* Due to the skewed nature of the dependent variable, a log-normal transformation was applied to the dependent variable.

$R^2 = 0.11$

-- Indicates no indirect path.

*p < .10*
shared a significant \((p < .10)\) positive relationship (.23) with the dependent variable, meaning that as local friendship networks increase, so too does the violent crime rate. And lastly, peer group affiliation had a significant \((p < .10)\) negative relationship (-.22) with the violent crime rate, meaning that as the level of control over teenage peer groups increases, the violent crime rate drops.

Results of Path Model 3 are presented in Table 10. Findings show the direct and indirect effects of endogenous and exogenous variables, based on official structural determinants data, as well as the zero-order correlation and the overall explained variance of the crime model, which accounted for 23% of the variation in the property crime rate. Socioeconomic status, residential mobility, family disruption, and peer group affiliation all shared significant relationships with the dependent variable which in this case was the property crime rate. Socioeconomic status had a significant \((p < .05)\) negative relationship (-.27) with the dependent variable. Residential mobility likewise shared a significant \((p < .05)\) negative relationship (-.27) with the dependent variable. Family disruption shared a significant \((p < .05)\) positive relationship (.26) with the dependent variable. Lastly, the endogenous variable of peer group affiliation shared a significant \((p < .05)\) negative relationship (-.24) with the violent crime rate.

Results of Path Model 4 are presented in Table 11. Findings show the direct and indirect effects of endogenous and exogenous variables, based on perceptual structural determinants data, as well as the zero-order correlation and the overall explained variance of the crime model, which accounted for 14% of the variation in the total crime rate. Only residential mobility shared a significant \((p < .10)\) relationship with the dependent
variable. The relationship was negative (-.28), meaning that as residential mobility goes up, the crime rate goes down.

Results of Path Model 5 are presented in Table 12. Findings show the direct and indirect effects of endogenous and exogenous variables, based on perceptual structural determinants data, as well as the zero-order correlation and the overall explained variance of the crime model, which accounted for 20% of the variation in the violent crime rate. Only socioeconomic status and residential mobility shared significant relationships with the violent crime rate. Socioeconomic status shared a significant ($p < .10$) negative relationship (-.25), while residential mobility had a significant ($p < .10$) negative relationship (-.34) with the violent crime rate.

Finally, results of Path Model 6 are presented in Table 13. Findings show the direct and indirect effects of endogenous and exogenous variables, based on perceptual structural determinants data, as well as the zero-order correlation and the overall explained variance of the crime model, which accounted for 11% of the variation in the property crime rate. Only residential mobility shared a significant ($p < .10$) relationship with the property crime rate. The relationship was negative (-.24).

In general, the traditional models of social disorganization outperformed the perceived models. In all three models, the official model explained more of the variance. The official model for total crime accounted for 27% of the variance compared to the perceptual model’s 14%. The violent crime official model accounted for over 33% of the variance compared to the perceptual model’s 20%. Lastly, the property crime’s official model explained 23% of the variance compared with only 11% for the perceptual model.
The official models also had more significant relationships between the independent variables and the dependent variable. For example, the official model for violent crime performed the best with five variables sharing significant direct relationships with the dependent variable. This, coupled with the higher overall $R^2$ values, leads us fail to reject our null hypothesis. Collectively, perceptual models do not outperform the official models in a traditional test of social disorganization theory.  

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Given the reasonable success of previous tests involving traditional models of social disorganization, we expected the models to perform better than they did, particularly the official models. Furthermore, some of the significant relationships that the models did possess were also suspect. For example, residential mobility shared a significant negative relationship with the crime rate in several of the models. The crime rate increasing when residential mobility decreases goes against much of the literature. Both of these examples may have been due to the low sample size ($n = 93$).
CHAPTER 6
DISCUSSION AND CONCLUSIONS

Findings from the current study have led to three important conclusions. First, although no clear definition of neighborhood and its boundary exist, most research dealing with neighborhood relies upon proxy measures defined by the administrative geographical boundaries of the U.S. Census in the form of blocks, block groups and tracks. However, current results suggest that individual perceptions about the size of one’s neighborhood consistently differ from administrative boundaries containing one’s neighborhood. In many cases, perceptual neighborhood boundaries contained multiple blocks, block groups, and tracts. Additionally, perceptual boundaries were found to vastly differ in size relative to their respective census block, and tract. These findings question the current practice of using administrative data to define neighborhood boundary. If administrative boundaries, specifically census data in this case, are inaccurate representations of neighborhood formation and boundary, it brings into doubt the usefulness of that data in acting as a proxy. In other words, if U.S. Census tracts, block groups, and blocks are an extremely poor representation of neighborhood boundary but are still used as proxies of such, how valid are the results gleaned from this data? Past research has struggled in finding an effective alternative to administrative boundaries. Given the findings of this study, evidence has been provided for the use of block groups as a reasonable proxy for neighborhood.

Second, the theory of social disorganization proposes that neighborhood structural characteristics influence crime with the help of several intervening variables which are reliant upon community dynamics. These community dynamics are mostly assumed to
be dependent upon the residents’ perceptual beliefs about the neighborhoods structural
condition. However, findings show that perceptual indicators of neighborhood structural
condition are consistently misaligned with official indicators. This could suggest that
residents are relatively inaccurate in their predictions of actual neighborhood conditions.
Or, it could mean that official data, aggregated to census boundaries, are not valid
indicators of actual neighborhood condition experienced by individuals within those
respective communities. If the latter is true, findings call into question results of
contemporary social disorganization research using official indicators of neighborhood
structural determinants of crime and delinquency.

Just as with boundary information, a similar question is brought forth from these
findings about the methodology used in past research. If official data on neighborhood
condition are significantly different than how people perceive conditions to be within
their neighborhood, how does this affect their behavior and action? If the deterioration of
neighborhood condition should negatively affect the level of social control within a
particular neighborhood, but neighbors in that area perceive conditions to be vastly
different than those reported in official statistics, the relevancy of official data in relation
to individual action seems poor.

Lastly, while official neighborhood boundaries and structural characteristics are
shown to offer a limited explanation of actual individual perceptions, the official data
performs better than perceptual data, in terms of $R^2$, when estimated in a traditional
model of social disorganization. This may very well be a matter of minimal sample size.
However, it shows that official data may, in fact, be more effective than respondent
provided data in explaining the variation present in the relationship between structural
measures and crime. Further research will be needed on this topic to fully confirm this suspicion.

Another possible explanation for the inability of perceptual models to explain an adequate amount of variation in the relationship between perceptual indicators and crime lies in the nature of the crime data. Because the dependent variable for crime consisted of official data on calls for service, there may be a disconnect between perceptual indicators of social disorganization and official crime. It is foreseeable that resident perceptions may only be effective at explaining perceived crime levels, rather than official data. For this to be determined, a measure of residents’ perception of crime, perhaps in the form of a ‘fear of crime’ question, would need to be added to the respondent survey. That variable would need to replace the official crime dependent variable, and path models would have to be estimated using the new data. This would help determine if this explanation was the reason for the perceptual model outcomes.

One final note deals with the theory of social disorganization itself. This study focuses largely on the methodological issues behind the theory, and possible shortfalls that exist within them. It is entirely possible, however, that characteristics within the theory of social disorganization are at fault for some of these issues. Perhaps the macro level neighborhood dynamics described by Shaw and McKay in their original work begin to loose relevancy once paired with micro level concepts such as social cohesion and social control. In searching to meld the two, the ill fit may indeed be caused by the impossibility of their linkage. However, while it deserves mention, this discussion falls outside the original scope of this study and therefore will not be expanded upon in this research.
Study Limitations

Although insightful, current findings are subject to several limitations. First, due to a limited sample size, generalizability is admittedly an issue. As a thesis master’s project, the funding, time, and staff support necessary to conduct research and analysis on a large representative sample simply was not available. However, the aim of this study is merely to explore these questions in order to guide future research in the area. Therefore, the convenience sample of 116, while not representative of any larger population of respondents, was deemed partly sufficient to detect meaningful variation in responses to various indicators of neighborhood and neighborhood condition that were measured. However, one aspect of the study in which the sample size may have affected the overall outcome involved the testing of research hypothesis III. Results were only moderately significant, and this is largely thought to be due to the low sample size of 93 respondents. Further research will be needed to confirm this suspicion.

Second, in past research, traditional models of social disorganization using official data on neighborhood condition and respondent identified endogenous data have been able to successfully demonstrate a significant relationship between social disorganization variables and crime (Sampson & Groves, 1989; Vessey & Messner, 1999; Sun, Triplett, & Gainey, 2004). Given this, the fact that our traditional model provided a relatively weak relationship between the variables identified and local crime means that the results are likely due to some other factor. Additionally, the nature of the calls for service data limited the amount of available crime types for use. If this data was a poor representation of the crime present in our sample communities, then a relationship
would be difficult to demonstrate. Taken together, both of these issues could have played
a part in our model’s effectiveness.

Third, t-tests were performed to assess mean differences in measures of
neighborhood and neighborhood condition between neighborhoods. Within
neighborhood differences were not examined. To some degree, it is foreseeable that
residents’ perceptions of neighborhood boundary and structural determinants of crime
could conflict with others’ within the same neighborhood. This variation could be
important to note in determining perceptual impact on the overall neighborhood
condition. However, official data on neighborhood condition is aggregated to the
neighborhood proxy level. Because this study is interested in determining the validity of
official data in relation to perceptual indicators, perceptual data was aggregated in a
similar manner using averages and between community variation.

Fourth, the validity of the dependent variable (crime) is suspect due to the nature
of the data. Because the data consists of calls for service, it includes only crimes known
to police. However, research has shown that calls for service data may be linked to
neighborhood disadvantage (Baumer, 2002). It is therefore possible that the calls for
service are more of a reflection of this factor than of the actual level of crime.

Despite these limitations, results presented are important and meaningful in that
they can serve to guide future research.
## Appendix A
Respondent Survey

### Perceived Versus Official Measures of ‘Neighborhood’ and Social Disorganization: Assessing the Validity of Commonly Used Indicators

#### Section 1: Involvement in your neighborhood.

Q1: *In the past year*, how often have you attended a meeting for a local board, council, or organization that deals with any community problems? Would you say...
- □ Never
- □ Once
- □ 2-3 times
- □ About once a month
- □ More than once a month

Q2: *In the past year*, have you served in a voluntary capacity on any local board, council, or organization that deals with community problems?
- □ No
- □ Yes

#### Section 2: Informal activities in your community or neighborhood.

Q3: *In the past year*, have you gotten together informally with or worked with others in your community or neighborhood to try to deal with some community issue or problem?
- □ No
- □ Yes

Q4: How important do you consider voting to be? Would you say...
- □ Not very important
- □ Somewhat important
- □ Very Important

#### Section 3: People in your neighborhood.

Q5: Mine is a close-knit neighborhood.
- □ Strongly disagree
- □ Disagree
- □ Neither disagree nor agree
- □ Agree
- □ Strongly agree

Q6: People in my neighborhood are willing to help their neighbors.
- □ Strongly disagree
- □ Disagree
- □ Neither disagree nor agree
- □ Agree
- □ Strongly agree

Q7: People in my neighborhood do not share the same values.
- □ Strongly disagree
- □ Disagree
- □ Neither disagree nor agree
- □ Agree
- □ Strongly agree

Q8: People in my neighborhood can be trusted.
- □ Strongly disagree
- □ Disagree
- □ Neither disagree nor agree
- □ Agree
- □ Strongly agree

#### Section 4: Respondent characteristics.

Q9: What is your gender?
- □ Male
- □ Female

Q10: What is your age? _____ (in years)

Q11: What is your race & ethnicity?
- □ White, non-Hispanic
- □ Black, non-Hispanic
- □ Native American, non-Hispanic
- □ Asian/Pacific Islander, non-Hispanic
- □ Other, non-Hispanic
- □ Hispanic, any race

Q12: When did you move to your current residence? _____ / __________ (MM/YYYY)

Q13: With 0 representing completely rural and 100 representing completely urban, on a scale of 0 to 100, how would you rate the neighborhood in which you currently live? _____ (0= completely rural and 100= completely urban).

Please continue to the back side of the questionnaire
Section 5: Please indicate how likely people in your neighborhood would act in each of the following situations listed below.

Q14: If a group of neighborhood children were skipping school and hanging out on a street corner, how likely is it that your neighborhood would do something about it? Would you say it is...
   ☐ Very unlikely   ☐ Unlikely   ☐ Neither unlikely nor likely   ☐ Likely   ☐ Very likely

Q15: If some children were spray-painting graffiti on a local building, how likely is it that your neighbors would do something about it?
   ☐ Very unlikely   ☐ Unlikely   ☐ Neither unlikely nor likely   ☐ Likely   ☐ Very likely

Q16: If a child was showing disrespect to an adult, how likely is it that people in your neighborhood would scold that child?
   ☐ Very unlikely   ☐ Unlikely   ☐ Neither unlikely nor likely   ☐ Likely   ☐ Very likely

Q17: If there was a fight in front of your house and someone was being beaten or threatened, how likely is it that your neighbors would break it up?
   ☐ Very unlikely   ☐ Unlikely   ☐ Neither unlikely nor likely   ☐ Likely   ☐ Very likely

Q18: Suppose that because of budget cuts the fire station closest to your home was going to be closed down by the city. How likely is it that the neighborhood residents would organize to try to do something to keep the fire station open?
   ☐ Very unlikely   ☐ Unlikely   ☐ Neither unlikely nor likely   ☐ Likely   ☐ Very likely

Section 6: Finally, what are your opinions about your neighborhood.

Q19: Out of every 100 people living in your neighborhood, in your opinion, how many are... (Total must add to 100).
   White, non-Hispanic ______  Black, non-Hispanic ______  Native American, non-Hispanic ______
   Asian/Pacific Islander, non-Hispanic ______  Other, non-Hispanic ______  Hispanic, any race ______

Q20: Out of every 100 people age 15 years and over living in your neighborhood, in your opinion, how many are...
   currently married ______  divorced ______  separated ______  widowed ______  or never married ______
   (Total must add to 100).

Q21: Out of every 100 people age 25 and over living in your neighborhood, in your opinion, how many are college educated?

Q22: Out of every 100 people age 16 and over employed and living in your neighborhood, in your opinion, how many hold a professional or managerial positions at work?

Q23: Out of every 100 households in your neighborhood, in your opinion, how many have a household income of more than $60,000 a year?

Q24: Out of every 100 families that reside in your neighborhood, in your opinion, how many are headed by a single parent?

Q25: Out of every 100 housing units occupied in your neighborhood, in your opinion, how many house residents who have lived there for less than 10 years?

Q26: Out of every 100 housing units occupied in your neighborhood, in your opinion, how many are owned (versus rented) by the resident?
Appendix B
Survey Instructions Part 1

Title of Study: Perceived Versus Official Measures of “Neighborhood” and Social Disorganization: Assessing the Validity of Commonly Used Indicators

Part 1: Defining Boundaries

Survey Respondents:

(Read after Informed Consent is signed)

You are about to participate in the first portion of this survey (Part 1 of 2). In this part, you will be asked your home address so that the researcher may locate it on the map and ask you a question regarding your perceived neighborhood boundaries. Feel free to speak to the researcher at any time if you have any questions or comments.

(Give Address Card)

Please write your address on the ‘address card’ and give it to the researcher. This card will be returned to you once your address is located on the map, and your address will not be kept in any of the data files for this project.

(Take Address Card once completed.
Locate address on the map, add point, zoom to point, 1:10,000m scale.
Select info associated with block shape file and find associated tract, block group, block.
Turn on Editor, select block shape file, select free hand tool, close dialogue box.)

Now that I have located your address on the map, use the mouse to draw a boarder around the area which you feel defines your “neighborhood”. This may be comprised of blocks, or a grouping of streets, or even a few homes. Whatever you feel is your “neighborhood”. You may use streets to help shape your boarder, or any other physical landmark.

Ask if you need help.

(Export selected feature, save as shape file using naming convention.)
Title of Study: Perceived Versus Official Measures of "Neighborhood" and Social Disorganization: Assessing the Validity of Commonly Used Indicators

Part 2: Assessing Conditions

Survey Respondents:

(Read after boundary file has been saved)

You are about to participate in the final portion of this survey (Part 2 of 2). In the following questionnaire, you will be asked several questions about the neighborhood you have just defined on the map. Keep in mind that you are free to not answer any of these questions, if you so choose. As before, you are also encouraged to ask questions at any time throughout the process.

(Give survey)
BIBLIOGRAPHY


U.S. Census Bureau (2010a). Retrieved October 29, 2010 From:http://factfinder.census.gov/jsp/saffi/SAFFInfo.jsp?_submenuId=aboutdata_1&_pagId=censuses_surveys


Vessey, B. M. & Messner, S. F. (1999). Further testing of social disorganization theory:

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