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Structural Indicators of Index Crime Rates in Metropolitan Counties for 1990 and 2000

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Structural Indicators of Index Crime Rates in Metropolitan Counties

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ABSTRACT

This study examines the relationship between structural features common to research within social disorganization and strain theory frameworks of metropolitan counties in 1990 and 2000 and their crime rates. It hypothesizes that economic inequality, a measure of relative deprivation, will be a more consistent structural indicator of crime than poverty, a measure of absolute deprivation. Twelve independent structural variables based on 1990 and 2000 Census data are placed in ordinary least-squares regression models to predict crime rates for 10 different Uniform Crime Report types. Results support this hypothesis, as well as identify a number of other structural indicators that are consistently significantly correlated to crime as predicted by both theories. Finally, I discuss the potential for integration of social disorganization and strain theories, which appear to complement rather than contradict each other.

INTRODUCTION

Many criminological theories focus on how individual demographic characteristics such as race or sex affect someone's probability of becoming an offender, a victim, or both. These individually-focused, behavioral theories of crime, however, do not explain variations in crime rates between demographically similar areas at a particular time, or stability in crime rates of one area that has experienced significant demographic changes over time. Ecological or structural theories of crime, on the other hand, focus on the environment within which crime occurs, in an attempt to answer questions such as these. Developed in the early decades of the 20th century, interest in ecological explanations of crime had waned as late as the 1970s; however, in the past several decades there has been a marked increase in research on how structural attributes of communities affect crime. This study examines the relationship between common structural characteristics of communities theorized to affect crime rates. More specifically, it assesses the significance of relative economic deprivation (inequality) compared to absolute deprivation (poverty). Is economic inequality a more significant indicator of crime rates than poverty? Which other structural variables, if any, explain variations in crime rates between communities during the same time period?

This study is a set of two cross-sectional analyses of structural features of selected metropolitan counties in 1990 and 2000. These features include poverty, inequality, urbanization, residential mobility, community attachment, education, employment, family disruption, age structure, and racial heterogeneity. These features will be quantified for selected metropolitan counties, and regression models built for each of ten crime rates for each time period. This analysis will be used to determine the correlations between these structural components and crime, and test two existing ecological theories of crime: social disorganization and structural strain. Both theories predict that relative economic deprivation has a greater impact on crime than absolute deprivation; by controlling for more structural features, using specific crime rates (rather than categories of crime such as ‘violent’ or ‘property’) and creating identical sets of models for two distinct time periods, this study hopes to measure these impacts more extensively and precisely than existing research.

As mentioned above, this inquiry draws upon two ecological theories of crime: strain and social disorganization theories. Strain theory posits that crime results from a lack of legitimate means to achieve goals (in wealth, education, and other “status” categories). Robert Merton’s (1938) original conception of strain theory suggested that deviance is cause by a “blockage” in goal-seeking behavior, where individuals resort to alternative methods of goal achievement; Robert Agnew’s (1985) revised strain theory suggests that in addition to this frustration, there is an additional blockage of pain-avoidance behavior, or the inability to escape an undesirable situation. Social disorganization theory argues that crime is linked to the inability of a community to realize the common values of its citizens, enforce mechanisms of informal social control, and solve commonly experienced problems; such failures result in a lack of social cohesion or capital (Kornhauser 1978). Poverty, high mobility, and racial heterogeneity can weaken informal social control networks (Shaw and McKay [1942] 1969) as can family instability (Sampson and Groves 1989).

In this study there is a potential to significantly contribute to public policy concerning criminal justice, social welfare and community development. Currently, criminal justice policies are typically designed around behavioral theories, and focus on controlling an individual’s actions; for example, hiring more police officers or extending prison sentences are assumed to deter someone who is ‘at risk’ to commit a crime (typically a young, poor, minority male) from doing so, by increasing the chance he will be caught or punished more severely. However, like the theories they draw from, by concentrating on individuals and not the community, these policies do not get at the root of the problem: why does crime occur? Because demographically similar areas often have different levels of crime, and areas with significant demographic change can manifest relatively stable crime rates, it logically follows that demographics, individual or aggregated to the community level, are not the answer. Something in the structure of the community must be at work. If it can be shown that certain independent variables are more strongly correlated to crime rates than others (generally or to specific crimes like larceny), policies designed to combat crime could become more focused and effective. For example, if education is shown to be negatively correlated with aggravated assault, rather than trying to punish offenders more harshly after the fact, funding could instead be diverted to education programs in an effort to prevent aggravated assaults before they even occur.

This research seeks to answer two questions. How do economic inequality and poverty differ in correlating with crime rates? What other structural features of a community significantly effect crime rates? The primary hypothesis investigated is that economic inequality correlates more significantly with crime rates than poverty. Concerning the second question, it is hypothesized that racial composition, unemployment, family structure and residential mobility will also have significant correlations to crime rates. Two theoretical approaches will be used to explain crime, both falling within the ecological framework: social disorganization and structural strain.

LITERATURE REVIEW

Social disorganization and strain theories, developed in the first half of the 20th century, have enjoyed something of a revival during the last several decades. Both were conceived of as community-level theories of delinquency, hypothesizing that the structural features of places greatly influenced the actions of the individuals living within. While similar in this respect, each theory grew out of distinctly different sociological traditions, and as such imagined the mechanisms of influence to be quite different. Social disorganization suggests that certain structural features contribute to a lack of social cohesion and weaken the ability of the community to exercise social control over its members, providing an environment more amenable to crime. Strain theory, on the other hand, believes that structural components contribute to individuals' feelings of frustration and alienation from the community, resulting in higher motivation to commit crime. Both have significantly evolved since their conception, especially in the last 20 or 25 years, an examination of the beginnings, evolution and current status of each is necessary to understand the concepts and analysis that follow.

Social Disorganization

Social disorganization theorizes that the characteristics of a community contribute to or detract from the level of social attachment among residents as well as the ability to enforce formal and informal social control. It is generally understood to have originated with the work of Clifford Shaw and Henry McKay ([1942] 1969), who examined juvenile delinquency rates and urban ecological characteristics in the city of Chicago. They found that delinquency rates in the neighborhoods of Chicago had remained relatively stable between 1900 and 1933, in spite of significant demographic changes in these neighborhoods over time. A second important finding, upon which they based their theory of social disorganization, was that delinquency rates were negatively related to the distance from the central business district of Chicago. Because a strong positive correlation between distance from the center and neighborhood economic composition was also found, Shaw and McKay postulated that delinquency rates were negatively correlated with the economic status of communities.

Shaw and McKay did not conclude that economic status had a *direct* effect on delinquency (Bursik and Grasmick 1993:31-33), but believed that economic status was part of an ecological process that influenced delinquency indirectly. This argument was based on the ecological approach of Robert Park and Ernest Burgess, who presumed that neighborhoods resulted from a selective movement of the population into areas associated with particular economic, cultural, or occupational groups (Burgess 1925:54). They conceived of cities in terms of concentric zones, where the center of the city was the most attractive area, surrounded concentrically by the least attractive area, known as the ‘zone in transition,’ and several more areas increasing in economic status. The cheapest housing was located in the zone of transition which typically functioned as the initial residence for incoming immigrant groups. Park and Burgess hypothesized that because these areas were undesirable, residents would leave as soon as it was economically viable and create high rates of population turnover and racially heterogeneity. The pattern continued outward; each surrounding zone would have less turnover, more heterogeneity, and higher economic status than the last. Shaw and McKay believed it was population turnover and racial heterogeneity, prompted by economic forces, which contributed to the community failing to control, or meet the common goals of, its residents.

Much of the ecological research that followed Shaw and McKay concentrated on measuring the levels of association between crime and structural indicators of community composition without specifying causality (see Bursik in Sampson and Byrne 1986), which was seen as a major flaw in social disorganization theory. It was not until the late 1970s and early 1980s that social disorganization was defined explicitly as “the inability of a community structure to realize the common values of its residents and to maintain effective social controls," (Morenoff, Sampson, and Raudenbush 2001). Kasarda and Janowitz (1974) identify this approach as a 'systemic model,' in which the community is a complex system of social networks and associations based in family life and ongoing socialization mechanisms. The systemic model and Shaw and McKay's original social disorganization model share the assumption that structural barriers hinder the development of formal and informal social networks that contribute to solving common problems, but the method of contribution is through intervening variables, such as turnover discouraging primary relationships, leading to a lack of social control (Berry and Kasarda 1977), or heterogeneity hampering communication between residents, leading to a failure to solve community-wide problems (Kornhauser 1978:75). Since the development of the systemic model, several studies have been undertaken to examine the links between exogenous structural indicators, crime, and the intervening constructs of social disorganization linking them (Simcha-Fagan and Schwartz 1986; Sampson and Grove 1989; Sampson, Raudenbush, and Earls 1997; Cantillon, Davidson, and Schweitzer 2003), generally finding support.

Within this body of work, a number of structural variables have been found that consistently affect crime within a community. Shaw and McKay ([1942] 1969) initially used a number of variables to estimate the capacity of a community to exercise control (for a summary see Walker in Barak 1994) including population turnover, owner-occupied housing, vacant housing (all of which measure residential mobility), racial and ethnic heterogeneity, and poverty. Later studies have confirmed the effects of mobility, poverty, and heterogeneity (Kornhauser 1978), in addition to finding several other indicators of disorganization and related difficulties in establishing control. Sampson included family stability (from Sampson and Byrne 1986), theorizing that disrupted families can attenuate community social control, especially of youth.

Income inequality has been seen as discouraging communication across unequal income groups and inhibiting the establishment of social control (Sampson and Groves 1989; Barnett and Mencken 2002; Blau and Blau 1982). Finally, urbanization makes the creation of social networks more difficult (Sampson 1988; Kawachi, Kennedy, and Wilkinson 1999).

Strain

Strain theory developed in much the same way as social disorganization theory, drawing on an existing sociological tradition and modifying it to explain community differences in crime as a function of structure. Taking a page from Durkheim, Robert Merton (1938) applied the idea of anomie to a broader perspective. Where Durkheim had assumed that anomie was a function of the rapid social changes occurring during industrialization, Merton saw anomie as a permanent feature of modern society. Instead of defining anomie as the absence of norms, Merton posited that anomie occurred when there was a disjunction between goals and means. When opportunities to achieve goals, such as economic wealth or social status, were blocked, pressures and frustration are produced, i.e. strain, that lead to criminal behavior.

The sources of strain in Merton's work are found at the community-level. It is the community that establishes which goals its members should hope to achieve, while also defining the acceptable means employed by members to achieve them. As Merton noted, "when a system of cultural values extols, virtually above all else, certain common success-goals for the population at large while the social structure rigorously restricts or completely closes access to approved modes of reaching goals for a considerable part of the same population" (1938:211), a significant disjunction between goals and means occurs. Merton typically focused on the inability to achieve economic success, which could lead directly to criminal behavior by the individual seeking to attain the goal through illegitimate means. While Cloward and Ohlin

(1960) also focused on economic success as the goal, they posited that delinquency occurred as an outcome of strain only when both legitimate means to success were lacking and illegitimate means existed. Cohen (1955) agrees with this concept, but focuses not on economic success but the attainment of class status.

While there are aspects of the individual within strain theory, such as Merton’s typology of adaptations, it categorizes anomie, or alienation and frustration, as a social condition, and was initially designed to explain rates of crime across the social structure (Burton, Jr. and Dunaway in Barak 1994), concerning itself with the structural barriers that were conducive to creating strain like economic disadvantage and unemployment, not the individual’s experience of it (Bernard 1987). However, there were several major criticisms of traditional strain theory, including its focus on economic success as the normative goal being blocked, the implication that strain theory was only applicable to the lower class, and the failure to consider individual-level sources of strain.

Recent evolutions in strain theory build upon Merton’s original structure, but seat the source of delinquency in individual responses to strain. The work of Robert Agnew has been especially influential. His revised strain theory (1985) adds to traditional strain theory by hypothesizing that not only does strain result from the blockage of goal seeking behavior, but also from blockages in pain avoidance behavior, or the inability to escape from negative environments and stimuli. Negative environments that produce strain can include abusive family environments and negative school environments. Agnew, like several others (cf. Elliott and Voss 1974) also contended that the notion of ‘goals’ was variable; monetary gain and class advancement are not the only ones. This allows strain theory to be applied to the middle class and by extension the upper class, by implicitly introducing the concept of relative deprivation into strain theory. He explicates that if "goal commitment is a variable, one can argue that the middle class has higher aspirations and this offsets whatever advantage they might have in achieving goals" (Agnew 1985:153). This echoes earlier investigations into the links between strain and relative deprivation theory (Coser 1967).

Agnew further developed these ideas into what is now known as general strain theory (1992). Within this framework, criminal and non-criminal coping mechanisms may occur in reaction to three potential sources of strain: the failure to attain socially positive goals such as education, gainful employment, respect, and fair treatment (Agnew 1999), the restriction or denial of socially positive goals, and the presence of negative stimuli or forces (Burton, Jr. et al. 1994). It is not the structural features of a community that create strain directly influencing deviance, but the impact strain has on the individual and how the individual responds, such as with anger and aggressive forms of delinquency. This helps explain why "only *some* strained individuals turn to delinquency" (Agnew 1992:66). Like social disorganization theory, general strain theory implies a number of conditional variables such as anger, self-esteem and family attachment that influence form coping takes (Brezina 1998; Mazerolle and Piquero 1997, 1998; Mazerolle and Maahs 2000; Piquero and Sealock 2000). The availability of coping strategies themselves are also a determining factor in where strain results in delinquency; if no legitimate coping strategies exist, then it is more likely that illegitimate coping strategies will be used (Broidy 2001).

While strain theory investigations to date have focused on individual reactions to strain, typically adolescents, recent further advancements in strain theory have attempted to apply general strain theory to communities. As general strain theory is generally recognized as an important method in explaining crime at the individual level, Agnew (1999) has suggested that a macro-level version of general strain theory (sometimes known as MST) could be similarly applicable to explaining crime at the community level. Using some of the same variables as social disorganization theory, MST theorizes that exogenous community-level variables such as poverty, inequality, residential mobility and racial heterogeneity contribute to community-level strain. Unlike social disorganization, where the intervening variables acting between these structural features and crime are measures of social control and cohesion leading to disorganization, MST uses intervening variables representative of the three types of strain: failure to achieve goals, loss of positive stimuli, and presence of negative stimuli. In the only empirical test of MST, Warner and Fowler (2003) hypothesize that community characteristics indicative of disadvantage and residential mobility will increase levels of strain and higher strain will contribute to crime (in this case, violence known to survey subjects). They find that disadvantage factors (poverty, female headed households with children, racial composition and low education) and stability factors (residential stability and home ownership) significantly correlate with their measure of strain, in the expected directions.

Even more importantly, they also found that disadvantage and stability in the neighborhood significantly correlated with a measure of social control, also in the expected direction. This comes from to their third and fourth hypotheses: that strain adds to the prediction of crime over social control models, of which social disorganization is one, and that the effects of strain will be moderated by informal social control and social ties. Warner and Fowler find that both strain and informal control variables are significantly related to violence separately; however, when both are added to their model, social control is slightly below significance, while strain maintained its effect. Moreover, results were decidedly mixed on the interaction of strain and social control and social capital; while strain was positively associated with violence in communities with low social capital, in line with MST, strain was positively related to violence in areas with high social control, which is counterintuitive.

This is one of the first examinations of how social disorganization theory and strain theory can be tied together. It is logical to theorize that strain is more likely to result in a deviant outcome when levels of social control are weaker. Agnew (1999) suggests that community levels of strain are an additional, not alternative, explanation of community crime rates, and that “a full explanation of community differences in crime rates must draw upon a range of theories, including those which examine the ways in which communities motivate as well as control crime” (p. 147).

CONCEPTUAL FRAMEWORK

This research explores the relationships between structural characteristics of selected metropolitan counties and those counties’ index crime rates, as defined by the FBI’s Uniform Crime Reports (UCR). Specifically, it seeks to measure the difference between the effects of relative economic deprivation and absolute deprivation. There is an extensive body of research examining relationships between community structures contributing to strain and social disorganization and crime, whether by classes of crime (property or violent), specific types (like assault or murder), or the offender (such as juveniles). There is, nevertheless, a lack of quantitative analysis of these relationships during several time periods using both general crime rates alongside specific types of crime rates; additionally, little research exists that investigates these relationships from within the framework of both strain and social disorganization, often seen as mutually exclusive or competing theories. The independent or control variables used also tend to be different among studies. Blau and Blau (1982) examined the relationship between economic inequality, poverty and violent crimes for the year 1970. Chiu and Madden (1998) presented a general theoretical model regarding the relationship between economic inequality and property crime, specifically burglary. Morenoff, Sampson and Raudenbush (2001) focused on the correlation between concentrated economic disadvantage (among other independent variables) and homicide rates in Chicago neighborhoods during the mid-1990s; Bursik, Jr. and Grasmick (1993) similarly examined rates of juvenile delinquency and economic deprivation in 1960 and 1980 Chicago neighborhoods. Morgan Kelly's (2000) research on inequality and crime is a relatively comprehensive examination of the relationship between economic inequality and index crime rates, examining seven of the eight types of crime defined in the UCR (he excludes arson), but he only examines the correlations for one year of data, 1994. While each of these previous studies addresses the relationship between economic inequality and crime, they do so in a limited way. This study expands on existing research by comparing the applicability of strain and social disorganization theories to explaining crime rates for two identical periods of time. Very little research currently exists assessing the relative importance of each theory's explanatory variables on the same crime data, or the possibility of a synthesis of both theories.

Before describing the variables to be employed in this study, an important distinction between absolute deprivation (poverty) and relative deprivation (inequality) must be made. While the poverty rate is generally defined as the percentage of people in a given location who fall below a certain economic standard (in this case, a standard created by the U.S. Social Security Administration and the U.S. Office of Health and Human Services), inequality examines the stratification and distribution of resources within a given area, which in this case is income. Poverty measures economic disadvantage, while inequality measures the distance between the 'haves' and the 'have nots' in terms of income; social disorganization says that both poverty and inequality contribute to a decrease in community stability, while strain theory postulates that they creates frustration and alienation by blocking goals, leading to illegitimate means to meet goals, or crime. The distinction is important, because explanations of poverty cannot account for strain and social disorganization, and the crime they are believed to engender, in communities that are not impoverished.

The existing literature uses a number of independent and dependent variables when studying the relationship between structural composition and area crime rates. Among the independent variables used within this literature are measures of economic distribution, such as the Gini index and the Thiel coefficient, and the poverty rate. Other structural features used as independent or control variables include racial heterogeneity, levels of educational attainment, vacancy rates, unemployment rates, family structure, police activity, residential mobility, age distribution. As dependent variables, researchers use varying measures of crime or delinquency, including self-reported criminal activity, the number of juveniles referred to criminal justice systems, victimization surveys, or one or more specific classes or types of index crimes, such as homicide, burglary, rape, or violent vs. property crime (Baron 2004; Blau and Blau 1982; Chiu and Madden 1998; Ehrlich 1973; Harer and Steffensmeier 1992; Kelly 2000; Morenoff et al. 2001; Sampson and Groves 1989; Bursik, Jr. and Grasmick 1993).

This research considers *economic inequality* to be one of the primary independent variables and *poverty* as the other. Economic inequality is defined as the distribution of income across a given population; a population with a larger distribution between the poorest and richest residents of the subject area will receive a higher inequality rating. The measurement of inequality will be discussed in the next section. Poverty, as mentioned above, is measured by the percentage of residents falling below the U.S. standard poverty line.

A social disorganization framework hypothesizes that poverty significantly contributes to a decline in the ability of a community to establish common goals and impose social control on itself (Shaw and McKay [1942] 1969). Additionally, examinations of inequality's impact on social disorganization and crime theorize that inequality represents a situation where communication across very unequal income categories is more difficult, similar to the difficulties inherent in communication across racially heterogeneous groups (Sampson 1986; Sampson and Groves 1989; Barnett and Mencken 2002). Difficulties in communication inhibit the creation of community norms and the ability to establish formal and informal social control, thus leading to social disorganization and crime (Blau and Blau 1982).

Within strain theory, crime results from a blockage of legitimate means to attain socially established goals; while poverty represents a blockage to goals in the absolute sense, economic inequality should be more strongly related to crime than poverty, as it accounts for economic sources of strain in individuals who are not poor. An individual must be able to identify a cultural norm of achievement and success, and recognize that he or she does not have the resources to obtain these goals through legitimate means. This implies economic inequality, assuming that the goal to be achieved is economic success. Lacking a visible example of failure and the accompanying personal frustration, the pressure on one to obtain social and economic affluence will be greatly decreased (Merton 1938), which by extension would weaken poverty alone as a significant indicator of strain, and therefore, crime.

In addition to these two measures of deprivation, there are several other variables that are theorized to diminish social cohesion and control, create strain, or both. Urbanization represents the proportion of an area's population that lives within an urban area, typically a city or large town. It contributes to social disorganization in that friendship networks and social circles are decreasingly organized in a local fashion in urban communities (Sampson and Groves 1989). While some residents of urban communities may have very strong ties a small group, such ties can be restricted due to the population size inherent to an urban area, and also a lack of social 'buffers' within urban neighborhoods, like church groups and neighborhood associations (Kawachi et al. 1999). It is easier to know a few neighbors than many, especially when one's neighbors are very different from oneself. Racial heterogeneity creates disorganization in a similar fashion; it can be more difficult to establish a strong network of personal relations or community ties necessary to create common norms and values among a racially, ethnically or culturally diverse group (Cantillon et al. 2003). Racial discrimination can further compound this lack of cohesion by socially isolating minorities, while at the same time limiting the economic opportunities available and creating strain.

Family disruption is measured by the presence of 'traditional' (e.g., single without children, married couple with children) or 'non-traditional' (e.g., divorced/separated, single female with children) families. An area that contains a large number of 'disrupted' families can lack social control because it implies a lack of supervision and guardianship over both children (one's own children and others') and property within the community (Kawachi et al. 1999), as well as imply a lack of family commitment, leading to strain. Vacancy rates measure the proportion of housing units that are unoccupied for a majority of the calendar year, and suggest a measure of community attractiveness and attachment; areas with low social commitment (where residents want to move) will have higher vacancy rates (Shaw and McKay [1942] 1969). Owner-occupied housing, on the other hand, should be inversely related to social disorganization (and the related loss of social control and attachment), because it shows a commitment to remain in the community. This individual is not only a resident, but an investor.

Residential mobility is a measure of population turnover; high turnover indicates low commitment to a community, thus adding to social disorganization. A number of studies examining the relationship between length of residence and community attachment have a shown a strong positive correlation (Kasarda and Janowitz 1974; Sampson 1988). Because friendships and ties to the community take time to develop, longer residencies lead to more investment in and stronger identification with the community at large and it is this attachment that leads to more effective social control (Bursik, Jr. and Grasmick 1993). Moreover, it is more difficult in areas of high turnover to identify strangers, which means that criminal offenders can be more anonymous and fear of crime can be heightened, creating strain (Walker, in Barak 1994). Education measures the average of how much formal schooling a population has; communities evidencing lower education levels can encounter difficulty advancing economically, and thus create strain (Warner and Fowler 2003). Unemployment, when an individual is searching for but has no formal means of income, contributes to strain in the same way that lacking education does, by blocking legitimate or 'normal' economic progress (Rosenfeld, in Byrne and Sampson 1986). Finally, age structure is the distribution of ages within a population, e.g. teenagers or elderly as a proportion of the entire community; it is well-established that individuals in their late teens to early twenties are more likely to commit crime, but it is not clear if this probability is related to a lack of social bonds with the community (Rankin and Wells, in Barak 1994) or because they are more likely to react to strain through delinquency (Agnew and Brezina 1997).

The dependent variables in this study will be index crime rates, by type. In order to compile the data more easily, index crimes will follow the standards set by the FBI's UCR, meaning the rates will be calculated based on the number of reported offenses for a particular crime in a county (Federal Bureau of Investigation 2007). Simply put, "crime rates" (considered both categorically and comprehensively) will be conceptually defined as the incidence of crime per 100,000 people; for example, the rate of burglary per 100,000 inhabitants of the area under examination. There are eight specific types of crime examined here: murder, rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, and arson. In addition, total index crime rate and modified index crime rate will also be used; the total index includes seven of the specific crimes above but excludes arson, while the modified index includes all eight.

In a purely theoretical sense, each type of crime could have significant correlations with variables used in both theories. Social disorganization leads to a lack of cohesion and control, making it more difficult to monitor and discourage crime. Strain comes from goal blockage or pain avoidance blockage, and can lead to frustration and delinquent coping, increasing motivation to commit crime. Violent crimes (murder, rape, robbery and assault) are especially likely to be related to strain theory variables, as the anger and frustration strain engenders is more likely to result in the individual lashing out. Property crimes (burglary, larceny, auto theft and arson) are probably more likely to be related to social disorganization variables, as the lack of supervision makes it far easier to escape detection.

As stated previously, research of this type would not be unique, but certainly contribute to past studies examining the relationships between index crimes and structural characteristics of communities like economic inequality, poverty, residential mobility, and family structure, among others. By examining more specific relationships over two comparable periods of time, it will be easier to make generalized conclusions about the impact of poverty, economic inequality and other structural determinants on crime rates, whether total crime or a specific type. Available research often focuses only on one relationship, e.g. poverty and drug crime, inequality and arson, etc., making the conclusions drawn from the results much more difficult to generalize to a larger population. It is hypothesized here that economic inequality will predict all crimes more strongly than poverty, because poverty would not account for crimes that occur in communities that are not impoverished.

DATA AND METHODOLOGY

The purpose of this study is both evaluative and exploratory; it is at once generally testing the ability of social disorganization and strain theories to explain crime and more specifically examining the relative importance of economic inequality and poverty within these theoretical frameworks. The units of analysis used are metropolitan counties. Because smaller units such as neighborhoods are typically homogenous regarding aggregate measures of inequality, income, racial composition and education, conclusions based on smaller units of analysis are more limited in their generalizability; using a larger unit better accounts for area-wide trends. This is especially important when studying urban populations, as cities tend to become more homogenous as trends of outmigration to suburban areas continue.

The data available at the county level is more readily available and also more reliable because it can control for measurement and reporting error more easily. Within a smaller unit such as a census tract, missing or misreporting several cases will affect the reliability of the statistics produced much more than at the county level. Finally, the collection of the data is more standardized because it is performed by organizations which establish guidelines common to all reporting jurisdictions, whereas comparing data collected by a number of local agencies is more likely to have dissimilarities in collection and reporting procedures.

Economic inequality, poverty, urbanization, racial heterogeneity, family disruption, vacant housing, owner-occupied housing, residential mobility, education, unemployment and crime rates will be measured at two points in time: 1990 and 2000. The independent variables measuring ecological structural components of the metropolitan counties are calculated from the U.S. Census Bureau's 1990 and 2000 decennial census data, downloaded from Summary Tape File 1 and Summary Tape File 3 (U.S. Census Bureau 1990a, 1990b, 2000a, 2000b). Crime rate variables are based on data supplied by the Federal Bureau of Investigation's Uniform Crime Reports (U.S. Department of Justice 1989, 1990, 1991, 1999, 2000, 2001), a program established by the FBI in 1930 as a method of collecting, publishing and archiving national crime statistics. County-level data was not available directly from the FBI; however, the Inter-University Consortium for Political and Social Research has county-level statistics based on the original UCR data, which was also downloaded.

The population considered in this study is more populous, historically established metropolitan counties. These counties were chosen because of their stability over time; relatively short-term trends in population growth and turnover, economic fluctuations and other structural factors should affect this group less than more recently established smaller counties. The study sample selected all the component counties (and in several cases, cities) in 1990 and 2000 of metropolitan statistical areas (MSA's) that had a population of at least 500,000 in 1960. The six New England states, which use an alternative definition of 'metropolitan,' were excluded. The sample was further reduced by matching counties that qualified as MSA components in both 1990 and 2000. After compiling the data for these counties, an additional number were removed because they lacked enough UCR data to compute the three-year averages upon which the rates are based; at least two years from each period were required. Finally, two additional cases were removed: Williamsburg City, VA was removed after examining the univariate descriptive statistics because it was an outlier for many of the independent variables, while St. Louis City, MS was removed because it was a very large outlier for many of the dependent variables. Both were anomalies and clearly dissimilar from other older, larger metropolitan counties of interest to this study. Williamsburg City is a very small independent city, rather than a county. Many of its features, such as age structure, racial heterogeneity, and poverty, are strongly influenced by the population at the College of William and Mary. St. Louis City has abnormally high rates for several types of crime in 1990 and all but one of the rates in 2000; additionally, rather than evidence the national trend of decreases in crime for all types between 1990 and 2000, St. Louis City's rates *increased*. Finally, in Waukesha County, WI, the 2000 value for *% female hh* was missing, so the 1990 value was entered. The final sample includes 244 component counties and cities with no missing values.

Due to the nature of the data available and the design of the research sample, any conclusions drawn on such a large number of observations should be reliable. Both the Census and UCR are common sources of statistical data and are used often in the existing literature on crime and economics. However, Census data and UCR data can be flawed due to the possibility of missing information. Census data cannot be collected on the indigent, for example, and UCR data is collected from a variety of other agencies, not by the FBI itself, and misreporting can occur. Nevertheless, the Census is the most reliable and standardized source of demographic information available, and while the shortcomings of UCR data have been discussed at great length, researchers generally agree that the UCR is the best available measure of comparative frequencies of crime, though not of absolute frequencies (Blau and Blau 1982:120),. Definitional changes with the Census and UCR can also create problems in comparing data collected at different times, but these changes are rare and usually minor. This study uses approximately identical measures in both 1990 and 2000 with no major definitional changes occurring between time periods to maximize the comparability of the results of both analyses. Still, any generalizations made regarding the correlation between community structure and crime based on this study's results should be limited to metropolitan areas of similar size and age as the sample. No conclusions should be drawn about the relationships of the variables in a non-metropolitan population or for much smaller or more recently established metropolitan area components.

As stated previously, this study examines the relationship between structural characteristics of metropolitan counties and index crime rates, while focusing on the relative effects of economic inequality and poverty on crime. Already discussed are how 'poverty' and 'inequality' are different economic indicators: while economic inequality is conceptualized as the distribution of economic means across a population, it must now be operationalized it into a quantitative measure. Fortunately, there are many measures of economic inequality that have been developed from which to choose, including the Gini coefficient.

The Gini coefficient is a measure of income concentration based on the Lorenz curve, a function plotting a cumulative percentage of the population against the cumulative percentage of an asset (such as income or education) they possess and used to demonstrate the distribution of the asset in the population. For the Gini, a value of 0 indicates perfect equality and a value of 1 indicates perfect inequality. It is a ratio of the area between a theoretical 45 degree line depicting perfect equality and the Lorenz curve beneath it based on the actual distribution of income to the entire area beneath the 45 degree line, or twice the area between the Lorenz curve and the line of perfect equality (Allison 1978:872). The Lorenz curves for this study were created by dividing the population of a given county into approximately equal ranges of income, coded by midpoints, then plotting the cumulative proportion of the county population on the x-axis and the cumulative proportion of income on the y-axis. Figure 1 shows a hypothetical curve plotted in this manner: 'A' is the line of perfect equality and 'B' is the Lorenz curve.

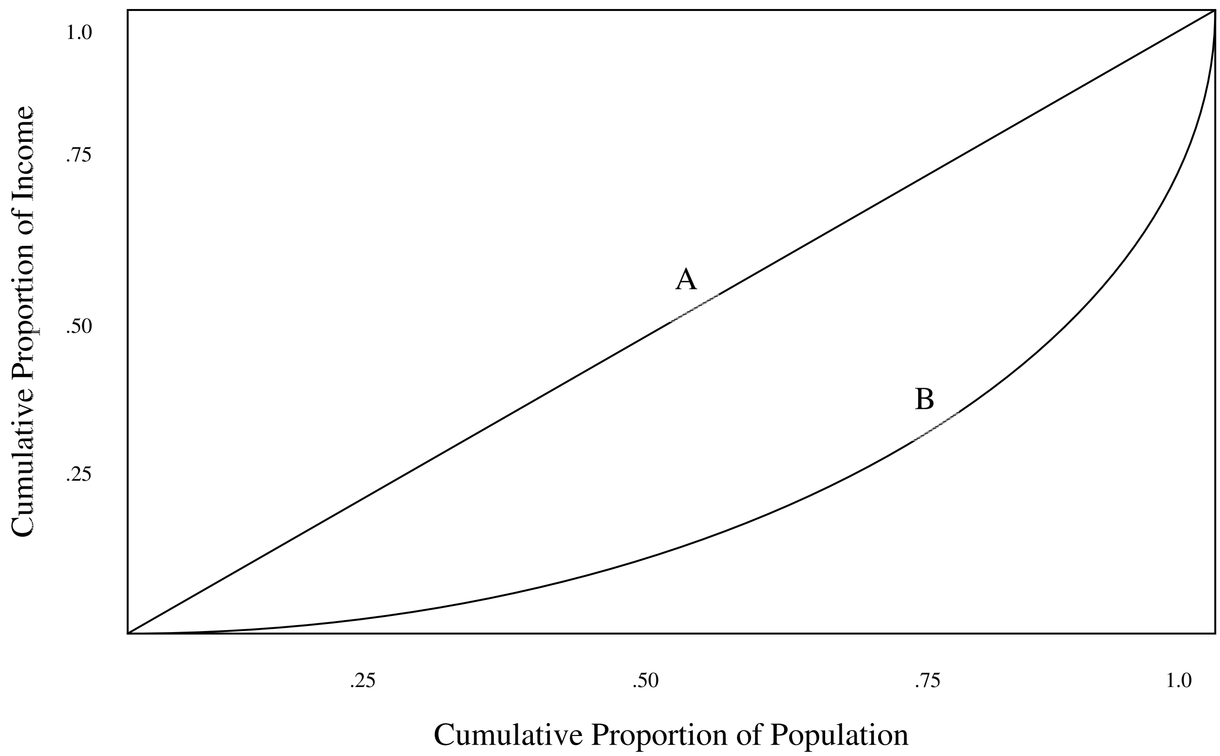

Figure 1. Theoretical Lorenz Curve

The Gini coefficient can also be seen as a measure of dispersion divided by twice the mean (Allison 1978: 867). The equation used to calculate the Gini for this study can be found in Appendix C.

Despite some disadvantages, as mentioned in the previous review of the literature, the Gini coefficient (*Gini*) has a number of strengths that recommend it as a measure of inequality. It is one of the most common inequality measures used in related research, which allows the results of this study to be compared more easily to others (cf. Blau and Blau 1982; Kelly 2000). The Gini also satisfies the principle of scale invariance, meaning that multiplying all the incomes in a given population by a constant leaves the inequality value unchanged (Allison 1978: 866), as well as the principle of transfers which argues that transfers of income from a poorer person to a richer one will increase the value of inequality (868).

Related to the variable of economic inequality is the other specific independent variable being examined, percentage of population below poverty (*% poverty*). Using U.S. Census data from 1990 and 200, *poverty* is operationalized for each county as a ratio of the number of people falling below poverty to the total number of people for whom poverty status was known for the previous year. Poverty status was defined in the Census data as having a household income above or below the national poverty line for the previous year, i.e. 1989 income determines poverty status in 1990, 1999 income in 2000.

The other independent variables discussed in the last chapter are urbanization, racial heterogeneity, family disruption, vacant housing, owner-occupied housing, residential mobility, education, unemployment, and age structure. They act as both control variables, in order to determine the relative importance of inequality and poverty on crime rates, and predictive variables. All of these are operationalized using data from the U.S. Census Bureau's decennial census, and like *poverty*, calculated to produce measures for 1990 and 2000 that are identical as possible, barring any radical changes in Census definitions of the base variables used.

Urbanization (*% urban*) is the ratio of county population designated as 'urban' in the Census to the total county population. Racial heterogeneity (*% white*) is the ratio of county population defined as 'white' (in the 1990 Census) or 'white alone' (in 2000) to total county population. While this is not a precise measure of racial heterogeneity, it is the simplest way to calculate the percentage of the population that is a racial minority. *% white* is used because changes in the reporting of race on the Census between 1990 and 2000 have affected this group the least. This measure still effectively estimates the effects of racial heterogeneity because both larger and smaller values can indicate more homogeneity; higher percentages point to homogeneity due to a majority white population, while smaller percentages also point to homogeneity, but due to a majority population of racial minorities.

Family disruption is measured as the presence of one type of 'non-traditional' family household (*% female hh*). It is the ratio of family households with children headed by a woman with no husband present to the total number of family households with children. Vacant housing (*% vacant*) is the ratio of vacant housing units to the total number of housing units in the county. Owner-occupied housing (*% owner*) is the ratio of owner-occupied housing units to the total number of housing units in the county. Residential mobility (*% same*) is the ratio of county residents at least five years old who lived in the same location five years before the census occurred to the total county population which is at least five years old.

Education (*% HS grad*) is the ratio of the population that is at least 25 years old who graduated high school to the total county population that is 25 years of age or older. Unemployment (*% unemployed*) is the ratio of the population at least 16 years old, in the labor force, and unemployed to the total population that is at least 16 years old and in the labor force. Finally, age structure is measured with two variables, designed to control for racial differences: *% white 15-24* and *% nonwhite 15-24*. The former is the ratio of the 'white' or 'white alone' population that is 15 to 24 years old to the total 'white' or 'white alone' population, while the latter is the ratio of 'nonwhite' population that is 15 to 24 years old to the total 'nonwhite' population.

The dependent variables in this study are the rates per 100,000 people of the eight index crimes used in the FBI's UCR program: murder, rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, and arson. The variable name for each is identical to the corresponding category of crime. Additionally, the total index rate (excludes arsons) and the total modified index rate (includes arsons) are included as well, labeled *index* and *mod. index*, respectively. Rates were calculated based on the number of offenses reported to the police for each county, which are available from the Inter-University Consortium for Political and Social Research. In order to control for short-term fluctuations in crime trends, three years of county-level UCR data was used for both the 1990 and 2000 analyses. The number of offenses reported for each of the ten categories was averaged over this three-year period, which was 'bracketed' around the decennial year. The rate per 100,000 people was then calculated by dividing 100,000 by the county population and multiplying the result by the three-year average. It is important to note here that five of the ten crime rates were normalized using the natural log (ln) transformation, designated by "*ln*" preceding the variable name, due to extreme kurtosis and skewness for both time periods: murder, robbery, aggravated assault, motor vehicle theft, and arson. These transformations will be explained further in the data analysis section.

Univariate and multivariate analyses were performed using the computer statistics package SPSS v.13.0 (SPSS). The multivariate analyses used ordinary least-squares regression models to determine the unique correlation of each of the 12 independent variables on each of the 10 crime rates for each of the two time periods. The results are used to test the primary hypothesis, that economic inequality is more strongly correlated with crime rates than poverty, both in total and by category of crime, as well as explore the ability of social disorganization and strain theories to explain crime rates in metropolitan counties in terms of their ecological/structural characteristics.

DATA ANALYSIS AND RESULTS

Univariate Statistics

Univariate descriptive statistics were produced at the outset in order to assess the appropriateness of the data for multiple regression analysis. Skewness and kurtosis values, as well as histograms, were examined to determine the normality of the distribution of each variable. Because of the size of the sample, less importance is placed on the statistical significance of skewness or kurtosis values; instead, the actual size of the statistic and the visual appearance of the distribution (as in a histogram) are better indicators of nonnormality (Tabachnick and Fidell 1996:73). The natural log transformation was run on any variable with unusual skewness or kurtosis to see if such a transformation significantly improved the distribution. Boxplots were also used to identify outliers and assess their impact. Once it was determined that the data were appropriate for multiple regression analyses, another set of descriptive variables was run, containing the variables in their final form. This output was reviewed for plausible means and standard deviations.

Skewness and kurtosis values of the independent variables were examined to estimate the normality of their distributions. As Tabachnick and Fidell point out, using normally distributed variables for multivariate analyses strengthens the results considerably (71). Significant positive or negative kurtosis can also result in an underestimation of the variance of a variable, though it is generally accepted that underestimation associated with negative kurtosis disappears in samples of at least 100 cases, while that associated with positive kurtosis disappears with samples of at least 200 cases (73). Since this sample has 244 cases, the effects of minor kurtosis are negligible.

All but two of the independent variables had relatively small skewness values, and all but three had relatively small kurtosis values; inspection of the distributions in histograms for each variable confirmed this assessment. The two variables that had higher than normal skewness values were 1990 *% nonwhite 15-24* (skewness = 3.605) and 2000 *% nonwhite 15-24* (skewness = 3.408). These two also had unusually large kurtosis values, as well as the variable 1990 *% white 15-24*: 1990 *% white 15-24* (kurtosis = 8.325), 1990 *% nonwhite 15-24* (kurtosis = 16.213) and 2000 *% nonwhite 15-24* (kurtosis = 16.873). Each of these variables was transformed using the natural log (ln) function, and the results examined for improved normality. For all three variables, the natural log transformation did not appreciably decrease the skewness or kurtosis values, nor did it change the shape of the distribution significantly, so they were left in their original form.

Outliers were assessed using boxplots of each independent variable. Any outliers found were examined to make sure that the data was entered accurately and that these cases were part of the population being studied. While there were a number of outliers for almost all of the independent variables, this is not unusual for a sample of this size (Tabachnick and Fidell 1996:67). It is typical for large samples to include a few cases with standardized scores over 3.29 ($p < .001$, two-tailed test); like with skewness and kurtosis, the size of this sample helps to compensate for their effects on the regression models. Not surprisingly, the three instances where there were a considerable number of outliers were the same three variables that had unusually high skewness and kurtosis values: 1990 *% white 15-24*, 1990 *% nonwhite 15-24* and 2000 *% nonwhite 15-24*. Boxplots of the previous natural log transformations performed on these variables showed that the transformation had little effect on the outliers.

Table 1 shows the mean, median, standard deviation, minimum, maximum, skewness and kurtosis values for the final independent variables. The means and standard deviations for all the independent variables were judged to be plausible. In 1990 the Gini coefficient had a mean of .391 (.037)[1]; in 2000, the mean was .397 (.036), indicating a slight increase in economic inequality within the sample between the two time periods. The percentage of urban population also increased, growing from a mean of .721 (.275) in 1990 to a mean of .789 (.220) in 2000. The percentage of the white population decreased, from a mean of .843 (.148) in 1990 to a mean of .792 (.169) in 2000. In 1990, the percentage of female headed households with children and no husband present had a mean of .186 (.077), which increased to a mean of .199 (.077) in 2000. Percentage of vacant housing units dropped from a mean of .076 (.035) in 1990 down to a mean of .061 (.027) in 2000. Owner-occupied housing percentages went up, increasing from a mean of .685 (.116) in 1990 to a mean of .704 (.119) in 2000. The proportion of residents who had remained in the same house rose from a mean of .527 (.079) in 1990 to a mean of .540 (.070) in 2000. The mean percentage of the sample population who had at least graduated high school also increased, from a mean of .780 (.075) in 1990 to a mean of .835 (.060) in 2000. Unemployment percentages dropped on average, with a mean of .054 (.019) in 1990 falling to a mean of .048 (.020) in 2000. The mean percentage of the population with income below the poverty line changed slightly, declining from a mean of .098 (.051) in 1990 to a mean of .091 (.048) in 2000. The means of both age structure variables decreased, with the percentage of whites between the ages of 15 and 24 falling from a mean of .136 (.018) in 1990 to a mean of .122 (.017) in 2000, while the percentage of nonwhites between the ages of 15 and 24 dropped an almost identical distance, from a mean of .182 (.049) in 1990 to a mean of .167 (.035) in 2000. There were 244 valid cases for all 12 independent variables.

[1] Standard deviations listed in parentheses

Table 1. Independent Variable Descriptive Statistics[a]

	Mean	Median	Std. Dev.	Min.	Max.	Skew.	Kurt.
1990 GINI	.391	.392	.037	.270	.516	.188	.647
2000 GINI	.397	.395	.036	.315	.512	.478	.411
1990 % URBAN	.721	.834	.275	.000	1.000	-.710	-.706
2000 % URBAN	.789	.870	.220	.090	1.000	-1.044	.245
1990 % WHITE	.843	.889	.148	.296	.995	-1.431	1.797
2000 % WHITE	.792	.833	.169	.213	.986	-1.137	.822
1990 % FEMALE HH	.186	.164	.077	.086	.506	1.692	3.658
2000 % FEMALE HH	.199	.177	.077	.088	.522	1.537	3.018
1990 % VACANT	.076	.066	.035	.029	.238	1.292	1.904
2000 % VACANT	.061	.055	.027	.015	.173	1.078	1.219
1990 % OWNER	.685	.716	.116	.179	.861	-1.397	3.078
2000 % OWNER	.704	.728	.119	.196	.880	-1.394	2.884
1990 % SAME	.527	.533	.079	.296	.721	-.140	-.317
2000 % SAME	.540	.543	.070	.343	.709	-.174	-.333
1990 % HS GRAD	.780	.785	.075	.576	.948	-.423	.036
2000 % HS GRAD	.835	.841	.060	.623	.970	-.574	.329
1990 % UNEMPLOYED	.054	.051	.019	.020	.133	.982	1.684
2000 % UNEMPLOYED	.048	.044	.020	.017	.143	1.536	3.682
1990 % POVERTY	.098	.087	.051	.022	.316	1.064	1.618
2000 % POVERTY	.091	.082	.048	.021	.307	1.367	2.744
1990 % WHITE 15 - 24	.136	.134	.018	.088	.248	1.743	8.325
2000 % WHITE 15 - 24	.122	.122	.017	.077	.207	1.155	4.253
1990 % NONWHITE 15 - 24	.182	.172	.049	.111	.498	3.605	16.213
2000 % NONWHITE 15 - 24	.167	.160	.035	.109	.408	3.408	16.873

[a] N = 244; SE Skew = .156; SE Kurtosis = .310

Once the independent variables univariate statistics had been evaluated, the dependent variables were similarly examined. It was found that five of the 10 crime rate variables consistently had relatively large positive values for both skewness and kurtosis. In the 1990 data, the murder rate had a skewness of 3.389 and a kurtosis of 16.920; in 2000, skewness = 3.020 and kurtosis = 12.344. The 1990 robbery rate had skewness = 2.572 and kurtosis = 6.738, while in 2000 skewness = 1.873 and kurtosis = 3.406. The 1990 aggravated assault rate had skewness = 1.653 and kurtosis = 3.031 and the 2000 rate had skewness = 1.310 and kurtosis = 1.467. The motor vehicle theft rate in 1990 had skewness = 1.678 and kurtosis = 2.618; in 2000 the rate had skewness = 1.625 and kurtosis = 2.679. Finally, the 1990 arson rate had skewness = 1.296 and kurtosis = 1.974, while the 2000 rate had skewness = 1.451 and kurtosis = 3.072. Visual examination of the histograms also pointed to nonnormal distributions.

The natural log transformation was performed on these five variables for each time period, and the results compared to the original values. It is important to note that because there were a handful of cases in the sample having murder and arson rates of zero for one or both time periods, the murder and arson rates for all cases in both sets of data were increased by 1. This prevented the natural log function from causing errors and producing missing values during the transformation and gave these cases a natural log value of zero. The skewness and kurtosis were reduced to absolute values below one for all five variables for both time periods, with the single exception of the 1990 natural log aggravated assault rate, where kurtosis = 1.018. Inspection of the histograms of the transformed variables confirmed the improved normality, and the transformed variables were retained for use in the multiple regression models. These transformed variables are distinguished in later analyses with “ln” prefixed to the variable name, in instances where the full variable label is not used.

Examination of the boxplots for the dependent variables produced results similar to those of the independent variables; a number of outliers were present for all of the dependent variables, but as explained earlier, that it to be expected in a sample of this size. Comparisons of the boxplots produced by the five transformed variables with boxplots of the original variable forms showed a marked decrease in the number and magnitude of outliers, further supporting the decision to use the transformed variables in the later regression models. During this assessment, St. Louis City, MS consistently appeared as an outlier for a number of the dependent variables, including the 1990 and 2000 index and modified index rates, 1990 and 2000 natural log murder rates, the 1990 rape rate, and the 1990 and 2000 burglary and larceny rates. Because the crime rate values for this component were so abnormal, the decision was made to remove it from the sample.

Table 2 shows the mean, median, standard deviation, minimum, maximum, skewness and kurtosis values for the final dependent variables. The means and standard deviations for all the dependent variables were judged to be plausible. In 1990, the natural log murder rate had a mean of 1.715 (.868)[2] which fell to a mean of 1.370 (.793) in 2000. The rape rate in 1990 had a mean of 33.218 (22.044), which also decreased in 2000, to a mean of 25.367 (15.291). The 1990 natural log robbery rate had a mean of 4.320 (1.447), dropping to a mean of 3.991 (1.350) in 2000. Natural log aggravated assault rate had a mean of 5.424 (.881) in 1990 and a mean of 5.103 (.906) in 2000, also evidencing a decline. The 1990 burglary rate had a mean of 1034.301 (578.727), dropping sharply in 2000 to a mean of 576.005 (322.258). The larceny rate in 1990 had a mean of 2808.614 (1321.685) which likewise fell to a mean of 2122.000 (977.887) in 2000. The 1990 natural log motor vehicle theft rate mean was 5.796 (1.007), also decreasing in 2000 to a mean of 5.441 (.970). The mean of the natural log arson rate in 1990 was 3.214 (1.048); the mean in 2000 was 2.841 (1.037). The total index crime rate in 1990 had a mean of 4916.543 (2676.105), falling in 2000 to a mean of 3416.786 (1745.108). The modified index crime rate was almost identical, having a mean in 1990 of 4952.676 (2692.375) and a mean in 2000 of 3441.511 (1757.843).

[2] Standard deviations listed in parentheses

Table 2. Dependent Variable Descriptive Statistics[a]

	Mean	Median	Std. Dev.	Min.	Max.	Skew.	Kurt.
1990 INDEX	4916.543	4343.092	2676.105	107.004	15104.582	.882	.660
2000 INDEX	3416.786	3132.233	1745.108	38.317	9126.403	.710	.246
1990 MOD INDEX	4952.676	4368.511	2692.375	107.495	15155.638	.874	.630
2000 MOD INDEX	3441.511	3140.335	1757.843	38.317	9154.263	.707	.233
1990 LN MURDER	1.715	1.660	.868	.000	4.347	.294	-.078
2000 LN MURDER	1.370	1.260	.793	.000	3.749	.517	-.091
1990 RAPE	33.218	28.838	22.044	.000	114.647	1.029	.990
2000 RAPE	25.367	22.895	15.291	.000	69.029	.678	.052
1990 LNROBBERY	4.320	4.250	1.447	.802	7.228	-.061	-.592
2000 LNROBBERY	3.991	4.045	1.350	-.324	6.528	-.412	-.023
1990 LN AGG. ASSAULT	5.424	5.509	.881	1.591	7.313	-.601	1.021
2000 LN AGG. ASSAULT	5.103	5.197	.906	1.923	6.794	-.652	.539
1990 BURGLARY	1034.301	948.599	578.727	26.997	2959.186	.833	.538
2000 BURGLARY	576.005	519.432	322.258	4.338	1775.766	.737	.417
1990 LARCENY	2808.614	2749.803	1321.685	52.927	7411.499	.577	.383
2000 LARCENY	2122.000	1942.233	977.887	19.520	4978.926	.557	.254
1990 LN MV THEFT	5.796	5.745	1.007	2.233	8.030	-.124	-.133
2000 LN MV THEFT	5.441	5.467	.970	1.873	7.403	-.569	.741
1990 LN ARSON	3.214	3.387	1.048	.000	5.062	-1.016	.935
2000 LN ARSON	2.841	3.059	1.037	.000	4.834	-.847	.330

[a] N = 244; SE Skew = .156; SE Kurtosis = .310

Multivariate Statistics

Once univariate analysis had confirmed that the data was appropriate for multiple regression, an ordinary least-squares regression model was constructed for each of the 10 crime rates for 1990 and 2000. Two diagnostics of multicollinearity were generated during this stage, tolerance and variance inflation factor (VIF). Multicollinearity occurs when independent variables are highly correlated, indicating that they contain redundant information (Tabachnick and Fidell 1996:84), or that one independent variable has a large proportion of its variability explained by the other independent variables (Norusis 2005:535). When calculating regression coefficients, multicollinearity inflates the size of the coefficients' standard errors, lowering the robustness of the model and resulting in coefficients failing to achieve statistical significance and Type II error (Tabachnick and Fidell 1996:86, 134). The tolerance statistic is a measure of the proportion of variability in an independent variable that is not accounted for by its linear relationships with the rest of the independent variables in the regression model. It is calculated by subtracting the squared multiple correlation (SMC) of a variable (acting as the dependent variable while the rest of the variables are independent variables) subtracted from 1 (134). This results in a statistic with a range between 0 and 1; lower values indicate higher multicollinearity. VIF is the inverse of tolerance; that is, 1/tolerance. Tolerance values approaching 0.1 or lower, and inversely, VIF values approaching 10 or more, may indicate a problem with multicollinearity (Norusis 2005:536).

In the models, only one independent variable was notably multicollinear, having a VIF value of over 10: *% poverty*. This is not surprising, as a bivariate analysis of the data show that poverty is strongly correlated to both the Gini coefficient and unemployment. However, multicollinearity cannot be assumed to indicate correlation; while it is certainly logical to assume that poverty correlates with the Gini coefficient and unemployment to some extent, it is also possible to have high poverty in the presence of low inequality (e.g. in a population where everyone is equally poor) and low unemployment (e.g. in a population where everyone is employed in poorly paying jobs). Poverty does measure something unique, and its inclusion in the models is justified.

The following tables report the unstandardized and standardized coefficients, t-values, and statistical significances for all the independent variables in each model, as well as the adjusted R^2 value and its statistical significance of the entire model. The unstandardized partial correlation coefficient, B, shows how much the value of the dependent variable changes when the value of the associated independent variable increases by 1 and all the other independent variables remain constant. Because the magnitude of the unstandardized coefficient is dependent on the unit of measurement of a given independent variable, however, B is not strictly comparable between variables in the same model. The standardized partial correlation coefficient, Beta, is the correlation coefficient when all the independent variables are standardized and expressed as z-scores (Norusis 2005:534-36), which allows an assessment of the relative importance of a given variable within the model. The t-value is the estimated coefficient of a given independent variable divided by its standard error, and the absolute value of the *t* indicates the number of standard deviations away from the mean. Adjusted R^2 differs slightly from R^2; R^2 is the proportion of variance in the dependent variable that is explained by all the independent variables, while the adjusted R^2 is an estimate of the proportion of variance in the dependent variable that would be explained by the independent variables using another data set from the same population (456). It adjusts for the expected inflation of the sample R, using the equation:

$$\tilde{R}^2 = 1 - (1 - R^2)\left(N - 1 \big/ N - k - 1 \right)$$

where N is the sample size, k is the number of independent variables, and R^2 is the squared multiple correlation coefficient (Tabachnick and Fidell 1996:164).

The first dependent variables to be examined are the natural log murder rates for 1990 and 2000. Mentioned above, these values reflect the natural logs of the murder rates per 100,000 people for each component county. In 1990 (see Table 3) the full model has an adjusted R^2 of .720, significant at the $p < .01$ level, indicating that an estimated 72% of the variance in the natural log of murder rates can be explained by variances in the independent variables. The Gini index (B = 3.782), % urban (B = .383), and % vacant housing (B = 3.284) had significant positive relationships, while % white (B = -2.554), % same house (B = -1.733) and % nonwhite 15-24 (B = -2.050) had significantly negative relationships. Beta values indicate that % white had the greatest impact on this model, with a value of -.435, followed by the Gini index (Beta = .160), % same house (Beta = -.157), % vacant housing (Beta = .133), % urban (Beta = .121) and % nonwhite 15-24 (Beta = -.115). The direction of the relationships of the Gini index, % white, and % same house support both strain and social disorganization explanations of crime, as each has been found to contribute to a lack of social cohesion and control in the community as well as increased strain at the individual level. The direction of the relationship for % nonwhite 15-24 was the opposite of expected, however. It was predicted that higher proportions of young people would contribute to social disorganization and that this group was more likely to react to strain in a delinquent manner; instead, it appears that there is a negative relationship to murder. However, it is possible that because of the serious nature of the crime itself, it is unlikely that people of this age would commit murder. There also appears to be a racial difference in the nature of the relationship between younger persons and murder, as it was only the percentage of nonwhites in the 15-24 age group that had a significant effect. The direction of the relationships of % urban and % vacant housing support the ideas of social disorganization, since the first inhibits the establishment of local networks of social control, while the latter indicates a lack of community commitment.

Table 3. OLS Model for Natural Log 1990 Murder Rates Per 100,000 in Selected Metropolitan Counties

Variable	B	*Beta*	t
(Constant)	**3.273****		3.229
GINI	**3.782***	*.160*	2.165
% URBAN	**.383***	*.121*	2.207
% WHITE	**-2.554****	*-.435*	-6.896
% FEMALE HH	**1.421**	*.125*	1.439
% VACANT	**3.284****	*.133*	2.996
% OWNER	**.167**	*.022*	.317
% SAME	**-1.733****	*-.157*	-3.049
% HS GRAD	**-.934**	*-.080*	-1.270
% UNEMPLOYED	**2.475**	*.055*	.709
% POVERTY	**.777**	*.045*	.386
% WHITE 15 - 24	**.128**	*.003*	.063
% NONWHITE 15 - 24	**-2.050****	*-.115*	-2.923

* p < .05 ** p < .01 Adjusted R^2 = .720**

Table 4 displays the same model for the natural log of the 2000 murder rates. The adjusted R^2 is slightly lower in 2000, with a value of .656, but it remains significant at the p < .01 level. An estimated 65.6% of the variance in the natural log of the murder rate is explained by variance in the independent variables. There are again six significant relationships, but they are not identical to those from 1990. The Gini index still has a positive correlation, but its strength within the model has fallen from the second strongest to the fourth (B = 4.409, Beta = .198). The other two positive relationships from 1990 are gone (% urban, % vacant housing), and two new positive correlations have appeared. The % female headed households (B = 3.525, Beta = .341) has become the strongest predictor within the model, while % owner occupied (B = 1.452, Beta = .217) is the third strongest. The three variables with negative relationships in the 1990 model remain: % white is now only the second strongest predictor (B = -1.438, Beta = -.306), % same house is the weakest significant predictor (B = -1.385, Beta = -.123) and % nonwhite 15-24 is slightly stronger (B = -3.656, Beta = -.163). Again, three of the variables that remained significant from the 1990 to the 2000 model (Gini, % white and % same house) are all supportive of both social disorganization and strain theory and the direction of the relationships was as expected; like the 1990 model, however, % nonwhite 15-24 has a negative relationship. The positive direction of the relationship of % owner occupied housing is contrary to social disorganization explanations, as it was expected to indicate stronger commitment to the community and better social control, leading to less crime, thought it is reasonable to think that murder is such a serious, violent crime that levels of social control effect it very little. Finally, whereas % urban was supportive of only social disorganization theory in 1990, % female headed households is found in both theories, as both an indicator of a loss in supervisory abilities within communities and a loss in family attachment that leads to strain. The direction of all the relationships was as expected except for % nonwhite 15-24; this is identical to what happened in the 1990 model, as explained above.

Table 4. OLS Model for Natural Log 2000 Murder Rates Per 100,000 in Selected Metropolitan Counties

Variable	B	*Beta*	t
(Constant)	**-.514**		-.453
GINI	**4.409***	*.198*	2.282
% URBAN	**.062**	*.017*	.281
% WHITE	**-1.438****	*-.306*	-4.229
% FEMALE HH	**3.525****	*.341*	3.851
% VACANT	**-.882**	*-.031*	-.559
% OWNER	**1.452****	*.217*	2.750
% SAME	**-1.385***	*-.123*	-2.556
% HS GRAD	**.075**	*.006*	.077
% UNEMPLOYED	**3.102**	*.078*	.872
% POVERTY	**2.813**	*.169*	1.149
% WHITE 15 - 24	**3.671**	*.081*	1.553
% NONWHITE 15 - 24	**-3.656****	*-.163*	-3.160

* $p < .05$ ** $p < .01$ Adjusted $R^2 = .656$**

Table 5 shows the model for 1990 rape rates per 100,000 people. The full model has an adjusted $R^2$of .548, estimating that 54.8% of the variance in rape rates is explained by variances in the independent variables, which is significant at the $p < .01$ level. Only three of the independent variables were significant in this model. The % female head of household had by far the strongest correlation (B = 173.665, Beta = .603), followed by % same house (B = -88.374, Beta = -.316) and % nonwhite population 15-24 (B = -55.958, Beta = -.123). The directions of the relationships between % female head of household and % same house to rape both support social disorganization and strain explanations. The negative direction of the relationship between rape and %nonwhite 15-24 is again the opposite of what strain or social disorganization would predict; like murder, however, rape may be such a serious crime that younger people are unlikely to commit it, at least as juveniles. It is possible that the relationship between juveniles (15-17 year olds) and rape and young adults (18-24 year olds) and rape are different, and by using a broader range of ages the results are being confounded. Also similar to the natural log murder models is the idea of a racial difference in age, because only the nonwhite group of 15 to 24 year olds had a significant relationship of any kind.

Table 5. OLS Model for 1990 Rape Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**-53.896**		-1.646
GINI	**75.391**	*.126*	1.336
% URBAN	**8.114**	*.101*	1.447
% WHITE	**5.455**	*.037*	.456
% FEMALE HH	**173.665****	*.603*	5.445
% VACANT	**9.443**	*.015*	.267
% OWNER	**33.064**	*.173*	1.942
% SAME	**-88.374****	*-.316*	-4.815
% HS GRAD	**26.927**	*.091*	1.134
% UNEMPLOYED	**132.435**	*.116*	1.176
% POVERTY	**42.159**	*.097*	.647
% WHITE 15 - 24	**117.576**	*.095*	1.802
% NONWHITE 15 - 24	**-55.958***	*-.123*	-2.471

* $p < .05$ ** $p < .01$ Adjusted $R^2 = .548$**

In 2000, the model for rape (Table 6) had a much smaller adjusted R^2 of .361, estimating that 36.1% of the variance in rape rates is attributable to variance in the independent variables, but this is still significant at the $p < .01$ level. Two significant relationships from the 1990 model remain: % female head of household and % same house. However, while the direction of the relationships is the same, supporting social disorganization and strain theories, the relative importance of these variables to the models has decreased. % female head of household now has the second largest correlation (B = 78.607, Beta = .394), while % same house is the third strongest in the model (B = -79.768, Beta = -.366). Three additional variables have become positively significant. % below poverty has the largest relative correlation in the model (B = 146.973, Beta = .457) and supports both social disorganization and strain theory explanations for rape. % owner occupied housing has the second smallest significant correlation to rape (B = 44.294, Beta = .344) and like murder, the positive direction of the relationship is contrary to a social disorganization theory of rape, where higher levels of owner-occupation should lead to community commitment and increased social control. However, also similar to murder, rape is such a violent crime that social control affects it very little; additionally, because rape is traditionally underreported and by nature, not public, there may be a decreased capacity for social control to affect it as well. Finally, the % high school graduates had the smallest relative significant impact on rape (B = 57.727, Beta = .226), but the positive relationship is supportive of strain theory explanations of rape, where the frustration and anger that come from goal blockage or pain avoidance blockage increase an individual's capacity for violence.

Table 6. OLS Model for 2000 Rape Rates Per 100,000 in Selected Metropolitan Counties

Variable	B	*Beta*	t
(Constant)	**-84.894****		-2.850
GINI	**73.881**	*.172*	1.455
% URBAN	**5.984**	*.086*	1.027
% WHITE	**7.287**	*.081*	.816
% FEMALE HH	**78.607****	*.394*	3.270
% VACANT	**.447**	*.001*	.011
% OWNER	**44.294****	*.344*	3.193
% SAME	**-79.768****	*-.366*	-5.601
% HS GRAD	**57.727***	*.226*	2.234
% UNEMPLOYED	**-74.881**	*-.098*	-.802
% POVERTY	**146.973***	*.457*	2.285
% WHITE 15 - 24	**84.602**	*.096*	1.362
% NONWHITE 15 - 24	**-9.695**	*-.022*	-.319

* p < .05 ** p < .01 Adjusted R^2 = .361**

The model of natural log 1990 robbery rates in Table 7 has an adjusted R^2 of .783 that is significant at the p < .01 level, estimating that 78.3% of the variance in the natural log of robbery rates can be explained by variance in the independent variables. Nine of the 12 independent variables were significant within this model. The largest relative correlation is with % urban (B = 2.320, Beta = .441), with a positive direction as predicted by social disorganization theory. The next largest correlation within the model was with % below poverty (B = -7.126, Beta = -.249); however, the negative direction of this relationship is the opposite of what social disorganization or strain theory would predict. Higher poverty should lead to less social control and more strain, resulting in more robbery; it is conceivable, however, that in an impoverished area there are fewer attractive targets for robbery, mediating the economic motivation inherent in robbery. % female head of household had the third largest relationship (B = 3.901, Beta = .206), followed by % white (B = -1.990, Beta = -.203), both of which are in the direction predicted by social disorganization and strain theories. Next is the negative relationship between % high school graduates and the natural log of robbery (B = -3.336, Beta = -.172), supportive of strain theory's idea of blocked opportunity leading to deviance; better education allows for more opportunity, as well as a larger capacity to escape situations, reducing strain and the motivation to deviate. The Gini index has the next largest correlation (B = 6.119, Beta = .156), the positive direction of which is supportive of both theories. The % owner occupied housing has the seventh largest relative effect (B = -1.913, Beta = -.153), supporting the social disorganization concept of increased commitment and social control inhibiting crime; % vacant housing, while having the smallest significant correlation (B = 3.718, Beta = .090), similarly supports social disorganization explanations. Finally, the negative correlation of % same house (B = -1.686, Beta = -.092), the relative size of which falls between the previous two variables examined, is supportive of both social disorganization and strain theories: higher residential stability increases social control, as well as decreasing strain, thereby lowering crime.

Table 7. OLS Model for Natural Log 1990 Robbery Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**6.442****		4.325
GINI	**6.119***	*.156*	2.385
% URBAN	**2.320****	*.441*	9.099
% WHITE	**-1.990****	*-.203*	-3.657
% FEMALE HH	**3.901****	*.206*	2.689
% VACANT	**3.718***	*.090*	2.309
% OWNER	**-1.913***	*-.153*	-2.470
% SAME	**-1.686***	*-.092*	-2.020
% HS GRAD	**-3.336****	*-.172*	-3.090
% UNEMPLOYED	**6.547**	*.087*	1.278
% POVERTY	**-7.126***	*-.249*	-2.406
% WHITE 15 - 24	**-1.330**	*-.016*	-.448
% NONWHITE 15 - 24	**-1.058**	*-.036*	-1.027

* p < .05 ** p < .01 Adjusted R^2 = .783**

Following the established pattern of the first several crime types, the adjusted R^2 of the model for natural log of robbery rates in 2000 (Table 8) is lower than in 1990, equaling .693.

This remains significant at the $p < .01$ level, estimating that 69.3% of the change in natural log robbery rates in 2000 is attributable to changes in the independent variables. However, four of the significant relationships from 1990 disappear. The % female head of household now has the largest relative effect (B = 6.042, Beta = .343), and the positive direction is again in the expected direction. % urban is now the second largest correlation in the model (B = 2.031, Beta = .331) and as before in the positive direction predicted by social disorganization. The correlation between % white and natural log of robbery rates is the third largest within the model (B = -1.658, Beta = -.207) and as in 1990 has the expected negative relationship. The Gini index also has the expected positive relationship (B = 7.194, Beta = .190) to natural log of robbery rates predicted by social disorganization and strain theories. Finally, the smallest significant effect, relative to this model, was from % same house (B = -2.609, Beta = -.135). The negative direction of this relationship is supportive of social disorganization and strain theories that hypothesize high residential mobility leads to diminished social control and increased strain on the individual.

Table 8. OLS Model for Natural Log 2000 Robbery Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**4.372***		2.397
GINI	**7.194***	*.190*	2.315
% URBAN	**2.031****	*.331*	5.694
% WHITE	**-1.658****	*-.207*	-3.031
% FEMALE HH	**6.042****	*.343*	4.105
% VACANT	**.136**	*.003*	.054
% OWNER	**-.184**	*-.016*	-.217
% SAME	**-2.609****	*-.135*	-2.992
% HS GRAD	**-2.843**	*-.126*	-1.797
% UNEMPLOYED	**.546**	*.008*	.096
% POVERTY	**-4.379**	*-.154*	-1.112
% WHITE 15 - 24	**-4.336**	*-.056*	-1.140
% NONWHITE 15 - 24	**.478**	*.012*	.257

* $p < .05$ ** $p < .01$ Adjusted R^2 = .693**

Table 9 shows the model for natural log aggravated assault rates in 1990. The adjusted R^2 is .500 and is significant at the $p < .01$ level, estimating that about 50% of the variance in the natural log of aggravated assault rates is explained by variance in the independent variables. Only three variables evidenced significant relationships with natural log robbery rates. The largest relative effect was from % urban (B = .980, Beta = .306), supporting a social disorganization explanation of crime, where the decreased capacity for community social control leads to higher crime. Also supporting a social disorganization explanation was the relative effect of % vacant housing, which was in the expected positive direction (B = 5.647, Beta = .225). The third significant variable was % high school graduate and negatively related to the natural log of aggravated assault (B = -2.431, Beta = -.206), consistent with the strain theory explanation that decreased ability to reach goals or escape negative environments leads to crime.

Table 9. OLS Model for Natural Log 1990 Aggravated Assault Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**6.275****		4.561
GINI	**4.143**	*.173*	1.748
% URBAN	**.980****	*.306*	4.162
% WHITE	**-.666**	*-.112*	-1.324
% FEMALE HH	**1.446**	*.126*	1.079
% VACANT	**5.647****	*.225*	3.797
% OWNER	**-.519**	*-.068*	-.725
% SAME	**-1.128**	*-.101*	-1.463
% HS GRAD	**-2.431***	*-.206*	-2.438
% UNEMPLOYED	**6.582**	*.144*	1.390
% POVERTY	**-3.090**	*-.177*	-1.129
% WHITE 15 - 24	**-1.599**	*-.032*	-.583
% NONWHITE 15 - 24	**-1.673**	*-.092*	-1.758

* $p < .05$ ** $p < .01$ Adjusted R^2 = .500**

In 2000, the model for natural log aggravated assault rates (Table 10) had an adjusted R^2 of .434, significant at the $p < .01$ level, suggesting that 43.4% of the variance in the natural log of aggravated assault rates is attributable to variance in the independent variables. Two new variables are significant in this model, the correlations of which support both social disorganization and strain explanations. % female head of household is the largest relative significant correlation (B = 3.319, Beta = .281) and is in the expected positive direction, while % same house has the third largest significant effect (-2.535, Beta = -.196) and is also in the expected negative direction. % high school graduates remains significant in the expected direction and has the second largest relative correlation to natural log of aggravated assault (B = -3.806, Beta = -.251), again supporting the concept of strain theory. Changing from the largest to the smallest relative correlation, % urban (B = .748, Beta = .182) again has the positive direction expected by social disorganization theory.

Table 10. OLS Model for Natural Log 2000 Aggravated Assault Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**7.725****		4.649
GINI	**2.301**	*.091*	.813
% URBAN	**.748***	*.182*	2.300
% WHITE	**-.505**	*-.094*	-1.012
% FEMALE HH	**3.319***	*.281*	2.475
% VACANT	**3.130**	*.095*	1.354
% OWNER	**.585**	*.077*	.756
% SAME	**-2.535****	*-.196*	-3.192
% HS GRAD	**-3.806****	*-.251*	-2.641
% UNEMPLOYED	**-3.051**	*-.067*	-.586
% POVERTY	**1.470**	*.077*	.410
% WHITE 15 - 24	**-4.232**	*-.081*	-1.222
% NONWHITE 15 - 24	**.520**	*.020*	.307

* p < .05 ** p < .01 Adjusted R^2 = .434**

The model for 1990 burglary rates seen in Table 11 has an adjusted R^2 of .683, explaining 68.3% of the variation in burglary rates through changes in the independent variables, which is significant at the p < .01 level. The largest relative correlation is with % vacant housing (B =

4813.124, Beta = .292) and in the positive direction social disorganization theory predicts. Social disorganization theory is also supported by the next largest relative correlation with % urban (B = 613.530, Beta = .291), because it is hypothesized that difficulties in establishing community networks inhibit social control, explaining the positive relationship between urbanization and crime. % same house has the third largest relative effect on burglary (B = -1977.751, Beta = -.270) and the negative direction is expected by both social disorganization and strain theories. The Gini index has the smallest relative significant correlation with burglary rates (B = 3502.268, Beta = .223) and is also supportive of both theories' predictions by having a positive relationship.

Table 11. OLS Model for 1990 Burglary Rates Per 100,000 in Selected Metropolitan Counties

Variable	B	*Beta*	t
(Constant)	**654.928**		.910
GINI	**3502.268****	*.223*	2.824
% URBAN	**613.530****	*.291*	4.977
% WHITE	**-444.347**	*-.113*	-1.689
% FEMALE HH	**770.856**	*.102*	1.099
% VACANT	**4813.124****	*.292*	6.184
% OWNER	**9.150**	*.002*	.024
% SAME	**-1977.751****	*-.270*	-4.901
% HS GRAD	**-960.680**	*-.124*	-1.841
% UNEMPLOYED	**2057.502**	*.069*	.831
% POVERTY	**600.630**	*.052*	.419
% WHITE 15 - 24	**1464.944**	*.045*	1.021
% NONWHITE 15 - 24	**-818.399**	*-.069*	-1.643

* p < .05   ** p < .01   Adjusted R^2 = .683**

The model for 2000 burglary rates (Table 12) is also significant at the p < .01 level, having an adjusted R^2 of .548 which indicates the model estimates that 54.8% of the variance in burglary rates is explained by variance in the independent variables. The largest relative effect is from % female head of household (B = 2195.623, Beta = .522) and the positive direction of the relationship supports both social disorganization and strain theories. % owner occupied housing has the next largest effect (B = 1068.384, Beta = .394), and is in the opposite direction predicted by social disorganization theory, which posits that stronger social control, indicated by more home ownership, should lead to less crime. One possible reason for the positive relationship between home ownership and burglary is that owned homes are more attractive targets for burglary because they indicate wealthier residents. The third largest relative effect on burglary is from % same house (B = -1702.979, Beta = -.371) and evidences the same negative relationship seen in the 1990 model supportive of both strain and social disorganization explanations of crime. The smallest relative significant effect is again from the Gini index (B = 3216.555, Beta = .356) and its positive relationship again supports both theories in that higher inequality leads to difficulties in establishing social control and also to strain.

Table 12. OLS Model for 2000 Burglary Rates Per 100,000 in Selected Metropolitan Counties

Variable	B	*Beta*	t
(Constant)	**-273.646**		-.518
GINI	**3216.555****	*.356*	3.576
% URBAN	**164.061**	*.112*	1.589
% WHITE	**-254.334**	*-.133*	-1.606
% FEMALE HH	**2195.623****	*.522*	5.154
% VACANT	**1376.435**	*.117*	1.874
% OWNER	**1068.384****	*.394*	4.347
% SAME	**-1702.979****	*-.371*	-6.748
% HS GRAD	**-864.144**	*-.160*	-1.887
% UNEMPLOYED	**-2462.273**	*-.152*	-1.488
% POVERTY	**-364.672**	*-.054*	-.320
% WHITE 15 - 24	**1081.376**	*.058*	.983
% NONWHITE 15 - 24	**192.899**	*.021*	.358

* $p < .05$ ** $p < .01$ Adjusted R^2 = .548**

Table 13 displays the model for 1990 larceny rates; the adjusted R^2 of .650 indicates that an estimated 65% of the variance in larceny rates is explained by variance in the independent variables, which is significant at the $p < .01$ level. The largest correlation in the model is % urban (B = 1798.379, Beta = .374) and the positive direction supports a social disorganization explanation. The second largest effect is from % female head of household (B = 4750.232, Beta = .275); this is also a positive relationship, which both social disorganization and strain theories predict. Both theories also predict the negative direction of the next largest correlation, % same house (B = -4076.469, Beta = -.243), because residential mobility contributes to a lack of social networks and control as well as strain. The two significant variables having the next largest effect in the model are in the direction predicted by social disorganization theory: % vacant housing (B = 7798.106, Beta = 207) indicates a lack of commitment to the community and inhibited social control, resulting in a positive relationship with crime, while % owner occupied housing (B = -1954.922, Beta = -.171) shows increased commitment and improved ability to establish control, leading to a negative relationship. The smallest significant effect in the model is from % white 15-24 (B = 8952.852, Beta = .121); the positive direction of the correlation is expected in both social disorganization and strain theories, but there is also an implicit racial difference in the effect of age on larceny, as only the % white 15-24 is significant.

Table 13. OLS Model for 1990 Larceny Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**2627.062**		1.521
GINI	**-712.356**	*-.020*	-.239
% URBAN	**1798.379****	*.374*	6.081
% WHITE	**-15.835**	*-.002*	-.025
% FEMALE HH	**4750.232****	*.275*	2.824
% VACANT	**7798.106****	*.207*	4.177
% OWNER	**-1954.922***	*-.171*	-2.177
% SAME	**-4076.469****	*-.243*	-4.211
% HS GRAD	**229.776**	*.013*	.184
% UNEMPLOYED	**-1263.144**	*-.018*	-.213
% POVERTY	**314.535**	*.012*	.092
% WHITE 15 - 24	**8952.852***	*.121*	2.601
% NONWHITE 15 - 24	**-902.317**	*-.033*	-.755

* $p < .05$ ** $p < .01$ Adjusted $R^2 = .650$**

Like the other analyses so far, the model for 2000 larceny rates (Table 14) has a smaller adjusted R^2 than its preceding 1990 counterpart, but is still significant at the $p < .01$ level. The adjusted R^2 for this model is .484 and estimates that 48.4% of the change in larceny rates is attributable to changes in the independent variables. % female head of household is now the largest relative significant correlation (B = 7301.668, Beta = .572), again in the positive direction expected within the social disorganization and strain theory frameworks. The % same house is also relatively more important than in 1990, having the second largest correlation in this model (B = -4723.989, Beta = -.339). Like before, this negative relationship is in line with the predictions of both theories. In the 2000 model, % unemployment becomes significant, having the third largest relative effect on larceny rates (B = -11799.622, Beta = -.240). This is the reverse of what strain theory predicts, because the blockage of goals inherent in employment should lead to higher crime; however, because the definition of unemployed used here implies that the individual is actively looking for work, it is possible that these people do not wish to jeopardize their ability to get new employment by committing a crime. % white 15-24 remains significantly related here, again in the positive direction expected by both theories (B = 10655.598, Beta = .190), and the implied racial difference remains with only % white 15-24 being significant. The smallest relative effect to be significant in this model is % urban (B = 732.262, Beta = .165); as before, it is in the positive direction expected by social disorganization theory.

Table 14. OLS Model for 2000 Larceny Rates Per 100,000 in Selected Metropolitan Counties

Variable	B	*Beta*	t
(Constant)	**466.709**		.273
GINI	**4199.414**	*.153*	1.440
% URBAN	**732.262***	*.165*	2.187
% WHITE	**-346.066**	*-.060*	-.674
% FEMALE HH	**7301.668****	*.572*	5.286
% VACANT	**1224.326**	*.034*	.514
% OWNER	**739.965**	*.090*	.929
% SAME	**-4723.989****	*-.339*	-5.773
% HS GRAD	**-419.946**	*-.026*	-.283
% UNEMPLOYED	**-11799.622***	*-.240*	-2.198
% POVERTY	**-2336.409**	*-.114*	-.632
% WHITE 15 - 24	**10655.598****	*.190*	2.986
% NONWHITE 15 - 24	**65.088**	*.002*	.037

* $p < .05$ ** $p < .01$ Adjusted $R^2 = .484$**

The model for natural log 1990 motor vehicle theft rates (Table 15) has an adjusted R^2 of .676 and is significant at the $p < .01$ level. The model estimates that 67.6% of the variance in the natural log of motor vehicle theft rates is explained by variances in the independent variables. The most influential significant variable in the model is % urban (B = 1.581, Beta = .432), the positive direction of which supports the social disorganization hypothesis that diminished ability to establish common social norms, and therefore, control, leads to more deviance. The second largest relative impact in the model of significance is from % below poverty (B = -6.606, Beta = -.332). The direction of this relationship is the opposite as predicted by either social disorganization theory or strain theory; higher poverty should detract from social control and create strain, and therefore increase crime. This result could be explained in the same manner as the negative relationship between poverty and robbery, since poorer areas may not contain as many attractive targets for motor vehicle theft. % white is the third largest significant correlation in the model (B = -1.698, Beta = -.249). Social disorganization and strain theories expect this to be a negative relationship. Strain theory also predicts the direction of the next largest significant correlation, % unemployed (B = 12.621, Beta = .242). However, this weakens the justification for the negative relationship between unemployment and larceny put forth previously, that people looking for work (as is implicit in the definition of unemployment used here) are less willing to risk job prospects by committing crime. The direction of the relationships between the least two influential variables of significance in this model are what social disorganization theory would expect. A higher value for % owner occupied housing (B = -1.609, Beta = -.185) increases mechanisms of commitment and social control and inhibits crime, while a higher value of % vacant housing (B = 4.186, Beta = .146) is an indicator of low community cohesion and lack of control, allowing crime to occur.

Table 15. OLS Model for Natural Log 1990 Motor Vehicle Theft Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**7.177****		5.667
GINI	**3.510**	*.128*	1.609
% URBAN	**1.581****	*.432*	7.291
% WHITE	**-1.698****	*-.249*	-3.669
% FEMALE HH	**.740**	*.056*	.600
% VACANT	**4.186****	*.146*	3.057
% OWNER	**-1.609***	*-.185*	-2.443
% SAME	**-.916**	*-.072*	-1.290
% HS GRAD	**-1.319**	*-.098*	-1.436
% UNEMPLOYED	**12.621****	*.242*	2.896
% POVERTY	**-6.606****	*-.332*	-2.622
% WHITE 15 - 24	**-1.021**	*-.018*	-.404
% NONWHITE 15 - 24	**-1.113**	*-.054*	-1.270

* $p < .05$ ** $p < .01$ Adjusted R^2 = .676**

Table 16 shows that a slightly different set of explanatory variables are significant in the model for the natural log of 2000 motor vehicle theft rates. The model has an adjusted R^2 of .571, approximating that 57.1% of the change in the natural log of motor vehicle theft rates is accounted for by changes in the independent variables. % female head of household is now significant, and is the largest relative correlation in the model (B = 4.698, Beta = .371). The positive relationship is as expected in both theories. The second largest relative significant variable in this model was also not significant in 1990; % same house (B = -4.450, Beta = -.322) has a negative correlation which again supports the concepts of both social disorganization and strain theories. % white is the third strongest significant correlation in this model (B = -1.084, Beta = -.189) and as in the 1990 model, has the negative direction predicted in both theories. The smallest relative impact of a significant variable is from % urban (B = .747, Beta = .170), which is again in the expected positive direction hypothesized by strain and social disorganization.

Table 16. OLS Model for Natural Log 2000 Motor Vehicle Theft Rates Per 100,000 in Selected Metropolitan Counties

Variable	B	*Beta*	t
(Constant)	**6.755****		4.358
GINI	**4.984**	*.183*	1.887
% URBAN	**.747***	*.170*	2.463
% WHITE	**-1.084***	*-.189*	-2.330
% FEMALE HH	**4.698****	*.371*	3.756
% VACANT	**-3.026**	*-.086*	-1.403
% OWNER	**.662**	*.081*	.918
% SAME	**-4.450****	*-.322*	-6.005
% HS GRAD	**-1.820**	*-.112*	-1.354
% UNEMPLOYED	**2.285**	*.047*	.470
% POVERTY	**-2.282**	*-.112*	-.682
% WHITE 15 - 24	**.261**	*.005*	.081
% NONWHITE 15 - 24	**-1.469**	*-.053*	-.929

* $p < .05$ ** $p < .01$ Adjusted R^2 = .571**

The final set of specific crime type analyses focus on the natural log of arson rates. Table 17 shows the model for 1990, which has an adjusted R^2 of .390, significant at the $p < .01$ level, which indicates the model estimates 39% of the variance in the natural log of arson rates is credited to variance in the independent variables. The most influential significant variable in this model is % high school graduate (B = 6.657, Beta = .473), and the direction of this relationship is not as predicted by strain theory; it was expected that lower education would increase strain and therefore crime. Strain theory does, however, predict the direction of the next largest significant correlation, % unemployed (B = 17.375, Beta = .320), as unemployment can create frustration and anger, leading to a deviant coping mechanism like arson. % urban has the third largest significant effect in the model (B = 1.005, Beta = .264), and the positive relationship is predicted by social disorganization theory. The last significant variable is % vacant housing (B = 4.262, Beta = .143), and its positive correlation offers further support for a social disorganization explanation of arson.

Table 17. OLS Model for Natural Log 1990 Arson Rates Per 100,000 in Selected Metropolitan Counties

Variable	B	*Beta*	t
(Constant)	**-2.406**		-1.331
GINI	**-4.518**	*-.159*	-1.451
% URBAN	**1.005****	*.264*	3.247
% WHITE	**-.528**	*-.074*	-.800
% FEMALE HH	**1.398**	*.102*	.794
% VACANT	**4.262***	*.143*	2.181
% OWNER	**-1.332**	*-.147*	-1.417
% SAME	**1.679**	*.126*	1.657
% HS GRAD	**6.657****	*.473*	5.080
% UNEMPLOYED	**17.375****	*.320*	2.793
% POVERTY	**1.952**	*.094*	.543
% WHITE 15 - 24	**2.697**	*.046*	.749
% NONWHITE 15 - 24	**-.789**	*-.037*	-.631

* $p < .05$ ** $p < .01$ Adjusted R^2 = .390 **

The model for 2000 natural log of arson rates (Table 18) has a small adjusted R^2 compared to the rest of the models; its value is only .160. However, it remains significant at the $p < .01$ level, meaning that about 16% of the variance in the natural log of arson rates is explained by variance in the independent variables. There are five significant variables in the model, and strangely, none of them were significant in the 1990 model. The largest relative significant effect is from % owner-occupied housing (B = 3.330, Beta = .381), and the positive direction of the relationship is opposite of what social disorganization theory would predict. The second largest significant effect in the model is from % female head of household (B= 4.586, Beta = .339). This positive relationship is what would be expected within a social disorganization or strain framework. % urban had the next largest significant effect for the model (B = 9.198, Beta = .316), and in the direction predicted by social disorganization theory. Both strain and social disorganization theories predict the negative direction of the fourth largest relative significant correlation, % same house (B = -3.250, Beta = -.220). Finally, % white 15-24 has the smallest significant effect in the model (B = 10.875, Beta = .183), and it is in the direction hypothesized by both theories.

Table 18. OLS Model for Natural Log 2000 Arson Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**-4.382**		-1.891
GINI	**9.198***	*.316*	2.330
% URBAN	**.873**	*.185*	1.926
% WHITE	**-.337**	*-.055*	-.484
% FEMALE HH	**4.586***	*.339*	2.453
% VACANT	**1.320**	*.035*	.409
% OWNER	**3.330****	*.381*	3.087
% SAME	**-3.250****	*-.220*	-2.934
% HS GRAD	**1.012**	*.058*	.504
% UNEMPLOYED	**-3.582**	*-.069*	-.493
% POVERTY	**-2.389**	*-.110*	-.478
% WHITE 15 - 24	**10.875***	*.183*	2.252
% NONWHITE 15 - 24	**-1.291**	*-.044*	-.546

* $p < .05$ ** $p < .01$ Adjusted R^2 = .160**

The last two sets of analyses use composite measures of crime: the total index crime rate, which includes all the types of crime previously discussed excluding arson, and the modified index crime rate, which includes all eight types of crime. Table 19 displays the model for the 1990 index crime rates. The adjusted R^2 for the index crime rates is .748, significant at the $p < .01$ level; the model estimates that about 74.8% of the variance in the index crime rates is explained by variances in the independent variables. The largest significant effect in the model is from % urban (B = 2963.447, Beta = .304), and the positive relationship is supportive of a social disorganization explanation. The next most influential significant variable in the model is % female head of household (B = 9270.238, Beta = .265); both strain and social disorganization theory expect the positive relationship shown here. % vacant housing has the third largest significant effect in this model (B = 15376.398, Beta = .202), and social disorganization predicts the positive direction of this relationship. Within both frameworks, the negative correlation of % same house (B = -6482.778, Beta = -.191) is also in the correct direction. The negative direction of the fifth largest significant correlation in the model, % owner occupied housing (B = -4366.246, Beta = -.188) is expected within the social disorganization framework. The smallest significant impact in the model is from % white (B = -2207.274, Beta = -.122), and its negative direction supports both theories' predictions regarding racial heterogeneity. The model for the 1990 modified index rates is almost identical to the 1990 index rates model, so it will not be described here; the same independent variables are significant in the same directions, and the adjusted R^2 is only .001 higher; see Table 20 for specific B, Beta, and t-values.

Table 19. OLS Model for 1990 Index Crime Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**6410.202***		2.161
GINI	**7310.440**	*.100*	1.431
% URBAN	**2963.447****	*.304*	5.835
% WHITE	**-2207.274***	*-.122*	-2.037
% FEMALE HH	**9270.238****	*.265*	3.209
% VACANT	**15376.398****	*.202*	4.796
% OWNER	**-4366.246****	*-.188*	-2.832
% SAME	**-6482.778****	*-.191*	-3.899
% HS GRAD	**-2331.397**	*-.065*	-1.084
% UNEMPLOYED	**13970.585**	*.101*	1.369
% POVERTY	**-6944.936**	*-.131*	-1.177
% WHITE 15 - 24	**7992.878**	*.053*	1.352
% NONWHITE 15 - 24	**-2485.067**	*-.045*	-1.211

* p < .05 ** p < .01 Adjusted R^2 = .748**

Table 20. OLS Model for 1990 Modified Index Crime Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**6327.414***		2.123
GINI	**7168.218**	*.098*	1.396
% URBAN	**2986.323****	*.305*	5.852
% WHITE	**-2221.860***	-*.122*	-2.040
% FEMALE HH	**9332.394****	*.265*	3.215
% VACANT	**15393.913****	*.201*	4.778
% OWNER	**-4380.036****	-*.188*	-2.827
% SAME	**-6445.869****	-*.189*	-3.858
% HS GRAD	**-2191.718**	-*.061*	-1.014
% UNEMPLOYED	**14340.360**	*.103*	1.398
% POVERTY	**-6772.598**	-*.127*	-1.143
% WHITE 15 - 24	**8030.825**	*.053*	1.352
% NONWHITE 15 - 24	**-2505.221**	-*.045*	-1.215

* p < .05 ** p < .01 Adjusted R^2 = .749**

The model for the 2000 index crime rates (see Table 21) had an adjusted R^2 of .608, significant at the p < .01 level, and estimates 60.8% of the variance in index crime rates is accounted for by variance in the independent variables. The model included a slightly different set of significant correlations from the 1990 model. % female head of household was the strongest significant correlation in the model (B = 13437.141, Beta = .590), and the positive direction of this relationship is anticipated by both strain and social disorganization theories. The next largest significant correlation in the model is with % same house (B = -8252.204, Beta = -.332) and its negative direction is also predicted by both theories. The third largest significant relationship in the model is to the Gini index (B = 12311.211, Beta = .252), whose sign is likewise expected. % urban has the next largest significant correlation in the model (B = 1204.064, Beta = .152); social disorganization predicts the positive direction of this relationship. The last significant correlation in the model is % white 15-24 (B = 11792.004, Beta = .118), and both strain and social disorganization theories can explain the positive direction found; however, there is, as has been found before, an implicit racial difference in the impact of age on crime, as only % white 15-24 is significant in this model. Unlike the 1990 models for index and modified index crime rates, which were practically identical, the 2000 modified index crime rates model is slightly different from the 2000 index crime rates model. The modified index crime rates model (see Table 22) has an identical adjusted R^2 value, so the models estimates the same amount of variance in the crime rates, but there is an additional significant variable. In this model % owner occupied housing has the fourth largest significant effect (B = 2507.877, Beta = .169); while the B and Beta values only changed slightly for this variable between the index and modified index models, it became significant (though not by much). The direction of the relationship is opposite that expected from social disorganization theory as well; while further investigation into this anomaly was not possible during this research, this unusual finding should be noted.

Table 21. OLS Model for 2000 Index Crime Rates Per 100,000 in Selected Metropolitan Counties

Variable	**B**	*Beta*	t
(Constant)	**302.102**		.113
GINI	**12311.211****	*.252*	2.714
% URBAN	**1204.064***	*.152*	2.313
% WHITE	**-1459.600**	*-.141*	-1.828
% FEMALE HH	**13437.141****	*.590*	6.255
% VACANT	**2107.000**	*.033*	.569
% OWNER	**2442.971**	*.166*	1.971
% SAME	**-8252.204****	*-.332*	-6.485
% HS GRAD	**-2236.304**	*-.077*	-.968
% UNEMPLOYED	**-11794.879**	*-.135*	-1.413
% POVERTY	**-5319.523**	*-.145*	-.926
% WHITE 15 - 24	**11792.004***	*.118*	2.125
% NONWHITE 15 - 24	**-935.599**	*-.019*	-.344

* p < .05 ** p < .01 Adjusted R^2 = .608**

Table 22. OLS Model for 2000 Modified Index Crime Rates Per 100,000 in Selected Metropolitan Counties

Variable	B	*Beta*	t
(Constant)	**161.301**		.060
GINI	**12434.996****	*.252*	2.720
% URBAN	**1222.719***	*.153*	2.331
% WHITE	**-1463.426**	*-.141*	-1.819
% FEMALE HH	**13512.407****	*.589*	6.242
% VACANT	**2075.070**	*.032*	.556
% OWNER	**2507.877***	*.169*	2.008
% SAME	**-8287.939****	*-.331*	-6.463
% HS GRAD	**-2184.792**	*-.074*	-.939
% UNEMPLOYED	**-11848.689**	*-.134*	-1.409
% POVERTY	**-5183.891**	*-.140*	-.895
% WHITE 15 - 24	**11984.676***	*.119*	2.143
% NONWHITE 15 - 24	**-1001.354**	*-.020*	-.366

* $p < .05$ ** $p < .01$ Adjusted $R^2 = .608$**

DISCUSSION

At the conclusion of this study, there were four things that became apparent: (1) economic inequality was a more reliable indicator of crime rates than poverty, (2) structural conditions in the community other than economic inequality significantly correlated to crime, some of which were more consistently correlated than others, (3) certain types of crime were explained more completely with structural variables than others, and (4) there is significant potential for a synthesis of social disorganization and strain theories.

In regards to the primary hypothesis of this research, that economic inequality is a better indicator of crime than poverty, the results seem to support this idea. The measure of poverty used here was only significantly correlated with three of the crime rate measures: rape, the natural log of robbery, and the natural log of motor vehicle theft. In the case of rape, the sign of the relationship was positive, as expected; however, in the case of the natural logs of robbery and motor vehicle theft rates, the sign was negative, which was contrary to what both social disorganization and strain theories would have predicted. Moreover, the relationship between poverty and each of these crimes was only significant in one or the other of the time periods studied, never both. This reflects a flaw in the use of poverty as a predictor of crime within strain and social disorganization frameworks. On a theoretical level, the major criticism of poverty as an indicator of crime rates is something mentioned previously in this study: it reflects a narrow focus on crime as originating in the lower class. Poverty-related explanations of crime inherently ignore the substantial amount of crime that is generated by the middle- and upper-classes.

Economic inequality, as measured by the Gini index, on the other hand, was significantly correlated to four specific types of crime: burglary and the natural logs of murder, robbery, and arson. It was also significantly related to total index and modified index crime rates. Although the Gini index was only significantly correlated to the natural log of arson rates, index and modified index crime rates in the 2000 time period, it was significant in both 1990 and 2000 for the other three rates listed above. Further adding strength to the argument for the use of an economic inequality measure within strain and social disorganization frameworks is the fact that where inequality was significant, it was always in the expected positive direction. Mirroring the theoretical consideration criticism of poverty already mentioned, inequality measures remove the focus on the lower-class; it is a construct that can be applied in a uniform way to all classes of economic means.

The second goal of this research was to explore what other structural variables mentioned in the social disorganization and strain literatures had significant correlations with crime rates, both by type and total. Every structural variable used was significantly correlated with several of the crime types, but some were far more consistently significant. Table 23 displays a crosstabulation of significant relationships; a plus sign indicates a positive correlation, a minus sign a negative one, and ‘NS’ means the relationship was not significant for that year. A blank field indicates the relationship was not significant for either time period. Relationships in 1990 are on the left, 2000 on the right.

Table 23. Significant Relationships

	GINI	% URBAN	% WHITE	% FEMALE HH	% VACANT	% OWNER	% SAME	% HS GRAD	% UNEMPLOYED	% POVERTY	% WHITE 15 - 24	% NONWHITE 15 - 24
INDEX	NS/+	+/+	-/NS	+/+	+/NS	-/NS	-/-				NS/+	
MODIFIED INDEX	NS/+	+/+	-/NS	+/+	+/NS	-/+	-/-				NS/+	
LN MURDER	+/+	+/NS	-/-	NS/+	+/NS	NS/+	-/-					-/-
RAPE				+/+		NS/+	-/-	NS/+		NS/+		-/NS
LN ROBBERY	+/+	+/+	-/-	+/+	+/NS	-/NS	-/-	-/NS		-/NS		
LN AGGRAVATED ASSAULT		+/+		NS/+	+/NS		NS/-	-/-				
BURGLARY	+/+	+/NS		NS/+	+/NS	NS/+	-/-					
LARCENY		+/+		+/+	+/NS	-/NS	-/-		NS/-		+/+	
LN MOTOR VEHICLE THEFT		+/+	-/-	NS/+	+/NS	-/NS	NS/-		+/NS	-/NS		
LN ARSON	NS/+	+/NS		NS/+	+/NS	NS/+	NS/-	+/NS	+/NS		NS/+	

For instance, % nonwhite 15-24 was only significant three times, two of which were for the same dependent variable (natural log of murder rates). Furthermore, for this particular independent variable, the sign of the relationship was in the opposite direction of expected all three times. Notably, when % nonwhite 15-24 was significant, % white 15-24 was not; this seems to contradict the general use of aggregate age categories at the community level as a factor in either social disorganization theory or strain theory, because there was a racial effect on the significance of age. The irregularity of the % below poverty variable has already been addressed.

It is also curious when examining the consistency of correlations that the two independent variables used that were specific to strain theory alone were rarely significant. % high school graduate was only significant five times within four types of crime, and the positive direction of the relationship was contrary to predicted for rape and arson; higher education averages aggregated at the community level should be indicative of lower levels of strain, through an increased ability to achieve positive goals and avoid negative stimuli, and therefore be negatively correlated with crime. The other strain-specific variable, % unemployed, was only significant three times, for three different crime types; additionally, the negative correlation with larceny rates was in the wrong direction. Similar to education level (although the measures are reversed), strain theory predicts that higher unemployment at the community level represents an inability to gain positive goals or avoid negative stimuli, so it should be positively correlated to crime all the time.

The three variables specific to social disorganization fared better when examining the consistency and direction of their significant correlations. % urban was significant for seven of the eight specific crime rates, as well as the index and modified index rates. Only for rape did it never become significant. Most importantly, the relationship was in the positive direction predicted by social disorganization theory in every case. The variable % vacant housing was also significant for every specific crime rate but rape, as well as both index rates, and the correlation was also in the predicted positive direction every time. However, this variable was significant only for the 1990 crime rates, and never for the 2000 rates. The regularity of this phenomenon is puzzling, and requires further investigation into general housing and crime trends between 1990 and 2000. The third social disorganization-specific variable, % owner-occupied housing, was significant for all the crime rates examined, including the index rates, except for the natural log of aggravated assault rates. The reliability of this measure is suspect, however, as it was never significant for the same crime rate variable in both 1990 and 2000. Additionally, the direction of the relationship was inconsistent; for rape, burglary and the natural logs of murder and arson rates it was positive, which is counter to the social disorganization idea that higher commitment to the community increases social control and lowers crime.

The remaining three variables to be discussed, which are used within both strain and social disorganization frameworks, were all remarkably consistent. % white was significantly correlated in the expected negative direction with the natural logs of murder, robbery and motor vehicle theft rates for both the 1990 and 2000 analyses; it was also negatively significant in 1990 for the index and modified index rates, but not in 2000. The measure of residential stability, % same house, was significantly correlated for every crime rate used, for both time periods, with the exception of the natural logs of aggravated assault, motor vehicle theft and arson rates in 1990, and always in the predicted negative direction. Finally, % female head of household was significantly and positively related to all the crime types for both years, with several more exceptions, all in the 1990 analyses: burglary rates and the natural logs of murder, aggravated assault, motor vehicle theft and arson rates. This consistency of these structural features of communities significantly correlating with crime gives strength to ecological notions of crime, although it is impossible to tell within this study which mechanisms are at work, strain or social disorganization.

The third general observation of this study is that certain crime rates are more likely to be consistently correlated to structural features. While there was a consistent decrease in the adjusted R^2 of the models between 1990 and 2000 for all ten of the dependent variables, there was also a regular pattern within time periods regarding which models had the larger adjusted R^2. The models for the natural log of robbery rates had the largest adjusted R^2 in both 1990 and 2000, followed by the index and modified index rates, again in both time periods. The natural log of arson rates always had the smallest R^2. It is possible that arson specifically was affected by significant differences in reporting methods of local and community institutions. More so than the other seven crime types, the procedures used to identify and report cases of arson can be quite different between reporting jurisdictions depending on factors such as expertise, evidence, and individual judgment. This suggests that community-level structural explanations are better suited to explain some crimes rates than others.

Finally, it is clear that structural explanations of crime are a valuable tool in the study of crime and its causes. However, there is a caveat to this statement. This study by design was unable to control or account for the intervening variables posited by both strain and social disorganization theories. There was no way to measure social disorganization or levels of social control, or strain, directly; the survey methodology normally used to quantify these concepts was beyond the scope of this study. This research cannot specifically claim that the independent structural variables used here have either direct or indirect effects on crime, nor can it test to see which theory, strain or social disorganization, explains crime better. Instead, the results of this study indicate that the preliminary work in integrating these theories is a step in the right direction; the fact that the most reliable indicators of crime in this study are those which both theories hypothesize as important is an indication that they are compatible, not competing, explanations of crime. Logically, it makes sense to claim that social disorganization and strain influence and mediate each other. If motivating strains to commit delinquent acts don’t exist, then the level of social control does not matter; if no form of social control exists, then even a minimal amount of strain can have a serious impact on crime. It is a reciprocal relationship.

CONCLUSION

This study set out to examine the relationship between structural features of communities and crime rates. It was hypothesized that economic inequality, a measure of relative deprivation, would be a more reliable structural indicator of crime rates than poverty, a measure of absolute deprivation, and it was concluded that this hypothesis was valid. Furthermore, it was found that some structural components do have stable, significant correlations with crime rates, while certain types of crime were found to be better correlated with structural features in general.

While both social disorganization and strain theories were found to have merit, it is impossible to tell with this study whether it is mechanisms of disorganization, strain, or both that affect crime rates. Further study is needed on a smaller unit of analysis that allows for the measurement of such intervening variables as social cohesion, trust, informal and formal control, anger, goal blockage and others, and a more sophisticated method of analysis, such as structural equation modeling, should be used. The work of Warner and Fowler (2003) on an integrated theory of macro-level strain is an example of where such research should proceed.

Finally, by finding significant correlations between structural variables and crime rates, more general policies can be designed that control and inhibit crime at its structural sources. These policies would not be 'criminal justice' policies *per se*, but educational, economic, and urban development policies that by their nature affect crime at the community level. Such policies would serve a dual purpose. For example, from the standpoint of strain theory, economic inequality is a structural feature contributing to feelings of anger and frustration. An economic policy that lowers the income taxes of the underclass, and raises taxes of the upper class, would serve to redistribute economic means within the community, lowering inequality and decreasing the amount of strain which could lead to crime. This same policy from a social disorganization standpoint would encourage more communication within the community and stronger social networks, and by extension social control, by minimizing the barriers to communication across economic strata.

Other such policies based on structural influences could address the issues of residential mobility and home ownership, which were both found to have a consistent effect on crime rates. Policies lowering property taxes could encourage residents to remain in the same location for a longer period of time, as could policies designed to improve the quality of education within the community. Lower interest rates on mortgages, as well as the aforementioned lowered property tax rates, would likely lead to increased rates of home ownership. Because the rate of female heads of household was so consistently significant, policies could be implemented that increase the ability of the community to supervise both children and property, something as simple as a Big Brother/Big Sister program, or Neighborhood Watch.

Instead of punishing offenders after the crime has already occurred, often at enormous expense, policies like these are designed to reduce the motivations to commit crime and increase the ability of communities to control crime from within. Since they serve to improve the community through better education, stronger social networks, less residential mobility, and other mechanisms, such policies are more efficient because they serve two purposes at once. While not designed to affect crime directly, they will do so in an almost secondary, derivative way.

APPENDIX A – METROPOLITAN COMPONENTS

FIPS CODE	Component	(Primary) Metropolitan Statistical Area
01009	Blount County, AL	Birmingham, AL MSA
01073	Jefferson County, AL	Birmingham, AL MSA
01115	St. Clair County, AL	Birmingham, AL MSA
01117	Shelby County, AL	Birmingham, AL MSA
04013	Maricopa County, AZ	Phoenix-Mesa, AZ MSA
05035	Crittenden County, AR	Memphis, TN-AR-MS MSA
06001	Alameda County, CA	Oakland, CA PMSA
06013	Contra Costa County, CA	Oakland, CA PMSA
06017	El Dorado County, CA	Sacramento, CA MSA
06037	Los Angeles County, CA	Los Angeles-Long Beach, CA PMSA
06041	Marin County, CA	San Francisco, CA PMSA
06059	Orange County, CA	Anaheim-Santa Ana, CA PMSA
06061	Placer County, CA	Sacramento, CA MSA
06065	Riverside County, CA	Riverside-San Bernardino, CA PMSA
06067	Sacramento County, CA	Sacramento, CA MSA
06071	San Bernardino County, CA	Riverside-San Bernardino, CA PMSA
06073	San Diego County, CA	San Diego, CA MSA
06075	San Francisco County, CA	San Francisco, CA PMSA
06081	San Mateo County, CA	San Francisco, CA PMSA
06085	Santa Clara County, CA	San Jose, CA PMSA
06113	Yolo County, CA	Sacramento, CA MSA
08001	Adams County, CO	Denver, CO PMSA
08005	Arapahoe County, CO	Denver, CO PMSA
08013	Boulder County, CO	Boulder-Longmont, CO PMSA
08031	Denver County, CO	Denver, CO PMSA
08035	Douglas County, CO	Denver, CO PMSA
08059	Jefferson County, CO	Denver, CO PMSA
11001	District of Columbia	Washington, DC-MD-VA MSA
12025-86	Dade County, FL	Miami-Hialeah, FL PMSA
12053	Hernando County, FL	Tampa-St. Petersburg-Clearwater, FL MSA
12057	Hillsborough County, FL	Tampa-St. Petersburg-Clearwater, FL MSA
12101	Pasco County, FL	Tampa-St. Petersburg-Clearwater, FL MSA
12103	Pinellas County, FL	Tampa-St. Petersburg-Clearwater, FL MSA
13013	Barrow County, GA	Atlanta, GA MSA
13057	Cherokee County, GA	Atlanta, GA MSA
13063	Clayton County, GA	Atlanta, GA MSA
13067	Cobb County, GA	Atlanta, GA MSA
13077	Coweta County, GA	Atlanta, GA MSA
13089	DeKalb County, GA	Atlanta, GA MSA
13097	Douglas County, GA	Atlanta, GA MSA
13113	Fayette County, GA	Atlanta, GA MSA
13117	Forsyth County, GA	Atlanta, GA MSA
13121	Fulton County, GA	Atlanta, GA MSA
13135	Gwinnett County, GA	Atlanta, GA MSA
13151	Henry County, GA	Atlanta, GA MSA
13217	Newton County, GA	Atlanta, GA MSA
13223	Paulding County, GA	Atlanta, GA MSA
13247	Rockdale County, GA	Atlanta, GA MSA
13255	Spalding County, GA	Atlanta, GA MSA
13297	Walton County, GA	Atlanta, GA MSA
15003	Honolulu County, HI	Honolulu, HI MSA

FIPS CODE	Component	(Primary) Metropolitan Statistical Area
17031	Cook County, IL	Chicago, IL PMSA
17043	DuPage County, IL	Chicago, IL PMSA
17089	Kane County, IL	Aurora-Elgin, IL PMSA
17197	Will County, IL	Joliet, IL PMSA
18011	Boone County, IN	Indianapolis, IN MSA
18019	Clark County, IN	Louisville, KY-IN MSA
18029	Dearborn County, IN	Cincinnati, OH-KY-IN PMSA
18043	Floyd County, IN	Louisville, KY-IN MSA
18057	Hamilton County, IN	Indianapolis, IN MSA
18059	Hancock County, IN	Indianapolis, IN MSA
18061	Harrison County, IN	Louisville, KY-IN MSA
18063	Hendricks County, IN	Indianapolis, IN MSA
18081	Johnson County, IN	Indianapolis, IN MSA
18089	Lake County, IN	Gary-Hammond, IN PMSA
18097	Marion County, IN	Indianapolis, IN MSA
18109	Morgan County, IN	Indianapolis, IN MSA
18127	Porter County, IN	Gary-Hammond, IN PMSA
18145	Shelby County, IN	Indianapolis, IN MSA
20091	Johnson County, KS	Kansas City, MO-KS MSA
20103	Leavenworth County, KS	Kansas City, MO-KS MSA
20121	Miami County, KS	Kansas City, MO-KS MSA
20209	Wyandotte County, KS	Kansas City, MO-KS MSA
21015	Boone County, KY	Cincinnati, OH-KY-IN PMSA
21037	Campbell County, KY	Cincinnati, OH-KY-IN PMSA
21111	Jefferson County, KY	Louisville, KY-IN MSA
22051	Jefferson Parish, LA	New Orleans, LA MSA
22071	Orleans Parish, LA	New Orleans, LA MSA
22089	St. Charles Parish, LA	New Orleans, LA MSA
22095	St. John the Baptist Parish, LA	New Orleans, LA MSA
22103	St. Tammany Parish, LA	New Orleans, LA MSA
24003	Anne Arundel County, MD	Baltimore, MD MSA
24005	Baltimore County, MD	Baltimore, MD MSA
24009	Calvert County, MD	Washington, DC-MD-VA MSA
24013	Carroll County, MD	Baltimore, MD MSA
24017	Charles County, MD	Washington, DC-MD-VA MSA
24021	Frederick County, MD	Washington, DC-MD-VA MSA
24025	Harford County, MD	Baltimore, MD MSA
24027	Howard County, MD	Baltimore, MD MSA
24031	Montgomery County, MD	Washington, DC-MD-VA MSA
24033	Prince George's County, MD	Washington, DC-MD-VA MSA
24035	Queen Anne's County, MD	Baltimore, MD MSA
24510	Baltimore city, MD	Baltimore, MD MSA
26087	Lapeer County, MI	Detroit, MI PMSA
26099	Macomb County, MI	Detroit, MI PMSA
26115	Monroe County, MI	Detroit, MI PMSA
26125	Oakland County, MI	Detroit, MI PMSA
26147	St. Clair County, MI	Detroit, MI PMSA
26163	Wayne County, MI	Detroit, MI PMSA
27003	Anoka County, MN	Minneapolis--St. Paul, MN--WI MSA
27019	Carver County, MN	Minneapolis--St. Paul, MN--WI MSA
27025	Chisago County, MN	Minneapolis--St. Paul, MN--WI MSA
27037	Dakota County, MN	Minneapolis--St. Paul, MN--WI MSA
27053	Hennepin County, MN	Minneapolis--St. Paul, MN--WI MSA

FIPS CODE	Component	(Primary) Metropolitan Statistical Area
27059	Isanti County, MN	Minneapolis--St. Paul, MN--WI MSA
27123	Ramsey County, MN	Minneapolis--St. Paul, MN--WI MSA
27139	Scott County, MN	Minneapolis--St. Paul, MN--WI MSA
27163	Washington County, MN	Minneapolis--St. Paul, MN--WI MSA
27171	Wright County, MN	Minneapolis--St. Paul, MN--WI MSA
28033	DeSoto County, MS	Memphis, TN-AR-MS MSA
29037	Cass County, MO	Kansas City, MO-KS MSA
29047	Clay County, MO	Kansas City, MO-KS MSA
29071	Franklin County, MO	St. Louis, MO-IL MSA
29095	Jackson County, MO	Kansas City, MO-KS MSA
29099	Jefferson County, MO	St. Louis, MO-IL MSA
29107	Lafayette County, MO	Kansas City, MO-KS MSA
29165	Platte County, MO	Kansas City, MO-KS MSA
29177	Ray County, MO	Kansas City, MO-KS MSA
29183	St. Charles County, MO	St. Louis, MO-IL MSA
29189	St. Louis County, MO	St. Louis, MO-IL MSA
34003	Bergen County, NJ	Bergen-Passaic, NJ PMSA
34005	Burlington County, NJ	Philadelphia, PA-NJ PMSA
34007	Camden County, NJ	Philadelphia, PA-NJ PMSA
34013	Essex County, NJ	Newark, NJ PMSA
34015	Gloucester County, NJ	Philadelphia, PA-NJ PMSA
34017	Hudson County, NJ	Jersey City, NJ PMSA
34027	Morris County, NJ	Newark, NJ PMSA
34031	Passaic County, NJ	Bergen-Passaic, NJ PMSA
34037	Sussex County, NJ	Newark, NJ PMSA
34039	Union County, NJ	Newark, NJ PMSA
36001	Albany County, NY	Albany-Schenectady-Troy, NY MSA
36005	Bronx County, NY	New York, NY PMSA
36029	Erie County, NY	Buffalo, NY PMSA
36047	Kings County, NY	New York, NY PMSA
36051	Livingston County, NY	Rochester, NY MSA
36053	Madison County, NY	Syracuse, NY MSA
36055	Monroe County, NY	Rochester, NY MSA
36057	Montgomery County, NY	Albany-Schenectady-Troy, NY MSA
36059	Nassau County, NY	Nassau-Suffolk, NY PMSA
36061	New York County, NY	New York, NY PMSA
36063	Niagara County, NY	Niagara Falls, NY PMSA
36067	Onondaga County, NY	Syracuse, NY MSA
36069	Ontario County, NY	Rochester, NY MSA
36073	Orleans County, NY	Rochester, NY MSA
36075	Oswego County, NY	Syracuse, NY MSA
36079	Putnam County, NY	New York, NY PMSA
36081	Queens County, NY	New York, NY PMSA
36083	Rensselaer County, NY	Albany-Schenectady-Troy, NY MSA
36085	Richmond County, NY	New York, NY PMSA
36087	Rockland County, NY	New York, NY PMSA
36091	Saratoga County, NY	Albany-Schenectady-Troy, NY MSA
36093	Schenectady County, NY	Albany-Schenectady-Troy, NY MSA
36103	Suffolk County, NY	Nassau-Suffolk, NY PMSA
36117	Wayne County, NY	Rochester, NY MSA
36119	Westchester County, NY	New York, NY PMSA
39023	Clark County, OH	Dayton-Springfield, OH MSA
39025	Clermont County, OH	Cincinnati, OH-KY-IN PMSA
39035	Cuyahoga County, OH	Cleveland, OH PMSA

FIPS CODE	Component	(Primary) Metropolitan Statistical Area
39041	Delaware County, OH	Columbus, OH MSA
39045	Fairfield County, OH	Columbus, OH MSA
39049	Franklin County, OH	Columbus, OH MSA
39055	Geauga County, OH	Cleveland, OH PMSA
39057	Greene County, OH	Dayton-Springfield, OH MSA
39061	Hamilton County, OH	Cincinnati, OH-KY-IN PMSA
39085	Lake County, OH	Cleveland, OH PMSA
39089	Licking County, OH	Columbus, OH MSA
39097	Madison County, OH	Columbus, OH MSA
39099	Mahoning County, OH	Youngstown-Warren, OH MSA
39103	Medina County, OH	Cleveland, OH PMSA
39109	Miami County, OH	Dayton-Springfield, OH MSA
39113	Montgomery County, OH	Dayton-Springfield, OH MSA
39129	Pickaway County, OH	Columbus, OH MSA
39133	Portage County, OH	Akron, OH PMSA
39153	Summit County, OH	Akron, OH PMSA
39155	Trumbull County, OH	Youngstown-Warren, OH MSA
39165	Warren County, OH	Cincinnati, OH-KY-IN PMSA
40017	Canadian County, OK	Oklahoma City, OK MSA
40027	Cleveland County, OK	Oklahoma City, OK MSA
40083	Logan County, OK	Oklahoma City, OK MSA
40087	McClain County, OK	Oklahoma City, OK MSA
40109	Oklahoma County, OK	Oklahoma City, OK MSA
40125	Pottawatomie County, OK	Oklahoma City, OK MSA
41005	Clackamas County, OR	Portland, OR PMSA
41051	Multnomah County, OR	Portland, OR PMSA
41067	Washington County, OR	Portland, OR PMSA
41071	Yamhill County, OR	Portland, OR PMSA
42003	Allegheny County, PA	Pittsburgh, PA PMSA
42007	Beaver County, PA	Beaver County, PA PMSA
42017	Bucks County, PA	Philadelphia, PA-NJ PMSA
42029	Chester County, PA	Philadelphia, PA-NJ PMSA
42045	Delaware County, PA	Philadelphia, PA-NJ PMSA
42051	Fayette County, PA	Pittsburgh, PA PMSA
42091	Montgomery County, PA	Philadelphia, PA-NJ PMSA
42101	Philadelphia County, PA	Philadelphia, PA-NJ PMSA
42125	Washington County, PA	Pittsburgh, PA PMSA
42129	Westmoreland County, PA	Pittsburgh, PA PMSA
47157	Shelby County, TN	Memphis, TN-AR-MS MSA
48029	Bexar County, TX	San Antonio, TX MSA
48039	Brazoria County, TX	Brazoria, TX PMSA
48085	Collin County, TX	Dallas, TX PMSA
48091	Comal County, TX	San Antonio, TX MSA
48113	Dallas County, TX	Dallas, TX PMSA
48121	Denton County, TX	Dallas, TX PMSA
48139	Ellis County, TX	Dallas, TX PMSA
48157	Fort Bend County, TX	Houston, TX PMSA
48187	Guadalupe County, TX	San Antonio, TX MSA
48201	Harris County, TX	Houston, TX PMSA
48251	Johnson County, TX	Fort Worth-Arlington, TX PMSA
48257	Kaufman County, TX	Dallas, TX PMSA
48291	Liberty County, TX	Houston, TX PMSA
48339	Montgomery County, TX	Houston, TX PMSA
48367	Parker County, TX	Fort Worth-Arlington, TX PMSA

FIPS CODE	Component	(Primary) Metropolitan Statistical Area
48397	Rockwall County, TX	Dallas, TX PMSA
48439	Tarrant County, TX	Fort Worth-Arlington, TX PMSA
48473	Waller County, TX	Houston, TX PMSA
51013	Arlington County, VA	Washington, DC-MD-VA MSA
51059	Fairfax County, VA	Washington, DC-MD-VA MSA
51073	Gloucester County, VA	Norfolk-VA Beach-Newport News, VA MSA
51095	James City County, VA	Norfolk-VA Beach-Newport News, VA MSA
51107	Loudoun County, VA	Washington, DC-MD-VA MSA
51153	Prince William County, VA	Washington, DC-MD-VA MSA
51179	Stafford County, VA	Washington, DC-MD-VA MSA
51199	York County, VA	Norfolk-VA Beach-Newport News, VA MSA
51510	Alexandria city, VA	Washington, DC-MD-VA MSA
51550	Chesapeake city, VA	Norfolk-VA Beach-Newport News, VA MSA
51600	Fairfax city, VA	Washington, DC-MD-VA MSA
51610	Falls Church city, VA	Washington, DC-MD-VA MSA
51650	Hampton city, VA	Norfolk-VA Beach-Newport News, VA MSA
51683	Manassas city, VA	Washington, DC-MD-VA MSA
51685	Manassas Park city, VA	Washington, DC-MD-VA MSA
51700	Newport News city, VA	Norfolk-VA Beach-Newport News, VA MSA
51710	Norfolk city, VA	Norfolk-VA Beach-Newport News, VA MSA
51735	Poquoson city, VA	Norfolk-VA Beach-Newport News, VA MSA
51740	Portsmouth city, VA	Norfolk-VA Beach-Newport News, VA MSA
51800	Suffolk city, VA	Norfolk-VA Beach-Newport News, VA MSA
51810	Virginia Beach city, VA	Norfolk-VA Beach-Newport News, VA MSA
53011	Clark County, WA	Vancouver, WA PMSA
53033	King County, A	Seattle, WA PMSA
53061	Snohomish County, WA	Seattle, WA PMSA
55079	Milwaukee County, WI	Milwaukee, WI PMSA
55089	Ozaukee County, WI	Milwaukee, WI PMSA
55109	St. Croix County, WI	Minneapolis--St. Paul, MN--WI MSA
55131	Washington County, WI	Milwaukee, WI PMSA
55133	Waukesha County, WI	Milwaukee, WI PMSA

APPENDIX B – DEPENDENT VARIABLES

The dependent variables in this study were crime rates, based on offenses reported to the police, calculated from the Federal Bureau of Investigation's Uniform Crime Report (UCR) program, as compiled by the Interuniversity Consortium for Political and Social Research (ICPSR). The ICPSR calculated the UCR statistics for the components of metropolitan statistical areas, which are not available from the UCR directly. Three-year averages were computed from 1989-1991 and 1999-2001 (in several cases it was a two-year average due to missing data) and from these rates per 100,000 people were calculated. For murder, robbery, aggravated assault, motor vehicle theft and arson the natural logs of these rates were used in the study. Below are the definitions of the ten crimes used as dependent variables.

Murder (criminal homicide) – A.) Murder and nonnegligent manslaughter: the willful (nonnegligent) killing of one human being by another. Deaths caused by negligence, attempts to kill, assaults to kill, suicides, and accidental deaths are excluded. The Program classifies *justifiable homicides* separately and limits the definition to (1) the killing of a felon by a law enforcement officer in the line of duty; or (2) the killing of a felon, during the commission of a felony, by a private citizen. B.) Manslaughter by negligence: the killing of another person through gross negligence. Deaths of persons due to their own negligence, accidental deaths not resulting from gross negligence, and traffic fatalities are not included in the category Manslaughter by Negligence.

Forcible rape — The carnal knowledge of a female forcibly and against her will. Rapes by force and attempts or assaults to rape, regardless of the age of the victim, are included. Statutory offenses (no force used - victim under age of consent) are excluded.

Robbery — The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.

Aggravated assault — An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm. Simple assaults are excluded.

Burglary (breaking or entering) — The unlawful entry of a structure to commit a felony or a theft. Attempted forcible entry is included.

Larceny-theft (except motor vehicle theft) — The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. Examples are thefts of bicycles, motor vehicle parts and accessories, shoplifting, pocket-picking, or the stealing of any property or article that is not taken by force and violence or by fraud. Attempted larcenies are included. Embezzlement, confidence games, forgery, check fraud, etc., are excluded.

Motor vehicle theft — The theft or attempted theft of a motor vehicle. A motor vehicle is self-propelled and runs on land surface and not on rails. Motorboats, construction equipment, airplanes, and farming equipment are specifically excluded from this category.

Arson — Any willful or malicious burning or attempt to burn, with or without intent to defraud, a dwelling house, public building, motor vehicle or aircraft, personal property of another, etc.

The rates for **Index Crime** are based on the total number of murder, rape, robbery, aggravated assault, burglary, larceny and motor vehicle offenses reported to the police. The rates for **Modified Index Crime** are based on the Index Crime totals plus the number of arsons offenses reported to the police.

APPENDIX C – INDEPENDENT VARIABLES

The independent variables used in this study were calculated from Census STF1 and STF3 data for the 1990 and 2000 decennial censuses. Below are the methods used to calculate each of the 12 independent variables from Census data categories for each metropolitan statistical area component.

Gini index – Income categories were constructed, recoded to midpoints, and using the equation

$$Gi = \left(\sum_{i=1}^{n} X_i Y_i + 1 \right) - \left(\sum_{i=1}^{n} X_i + 1 Y_i \right)$$

where X_i and Y_i are respective cumulative frequency distributions for income and population at each point in the distribution, and *n* is the number of class intervals (Shyrock and Siegel 1976:98)[3], Gini coefficients were calculated for each metropolitan statistical area component.

% urban – the population classified as urban divided by the total population

% white – the population classified as ‘white’ or ‘white alone’ divided by the total population

% female head of household, no husband present, with children – the number of households headed by females, with no husband present, with children, divided by the total number of households with children

% vacant housing – the number of housing units classified as vacant divided by the total number of housing units

% owner-occupied housing – the number of housing units classified as owner-occupied divided by the total number of housing units

% same house – the population classified as living in the same house 5 years earlier divided by the total population whose housing status 5 years earlier was known

% high school graduate – the population classified as high school graduates or higher divided by the total population whose education level was known

% unemployed – the population classified as in the labor force and unemployed divided by the total population whose employment status was known and in the labor force

% below poverty – the population classified as having an income below poverty the previous year divided by the total population whose poverty status for the previous year was known

% white 15-24 years old – the population classified as ‘white’ or ‘white alone’ from the ages of 15 to 24 divided by the total population classified as ‘white’ or ‘white alone’

% nonwhite 15-24 years old – the population classified as anything but ‘white’ or ‘white alone’ from the ages of 15 to 24 divided by the total population classified as anything but ‘white’ or ‘white alone’

[3] SAS code from this equation was produced by Philip N. Cohen, available at http://www.unc.edu/~pnc/gini.sas

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