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ABSOLUTE DEPRIVATION, RELATIVE DEPRIVATION, AND CRIME: A CHANGE-SCORE ANALYSIS OF STRUCTURAL COVARIATES OF CRIME

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ABSTRACT

In this thesis, I examine the relationships between absolute deprivation, relative deprivation, and crime rates in metropolitan counties in and between 1990 and 2000. Based on existing theoretical and empirical research, I investigate several questions. First, are the relationships between absolute and relative deprivation and crime significant, and is one type of deprivation a better indicator of crime than the other? Are the relationships stable after controlling for other theoretically relevant structural conditions? Finally, are the relationships the same at two time points, as well as over time? I employ cross-sectional analyses of the static relationships in 1990 and 2000 and change-score analyses of the relationships over the two decennial periods. The latter analyses add to the limited body of research examining the dynamic relationships between deprivation and crime. I measure county-level structural characteristics based on 1990 and 2000 Census data and use ordinary least-squares regression models to predict total, violent, property, and homicide crime rates. I then regress differences in crime rates from 1990 to 2000 on differences in the independent variables to examine the dynamic relationships between structural conditions and crime. The results of the cross-sectional analyses universally support the conclusion that absolute deprivation has a stronger association with crime than does relative deprivation. However, the change-score analyses indicate that not only do changes in levels of relative deprivation have stronger relationships than changes in absolute deprivation with shifts in crime levels, but that these relationships are unexpectedly negative. The implications of these results for theory and research are discussed.

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Introduction

While interest in ecological or structural theories of crime waned for a time, the past several decades witnessed a marked increase in theoretical and empirical research examining the relationship between communities and crime. This resurgence has been driven in part by the failure of micro-level criminological theories to explain variations in crime rates between demographically homogenous areas or communities at the same point in time, as well as stability in crime rates over time in areas that have experienced a significant amount of demographic change [(Bernard, Snipes, and Gerould 2010; Bursik and Webb 1982; Kawachi, Kennedy, and Wilkinson 1999; Kornhauser 1978), also see Shaw and McKay (1969) for a historical example of this critique]. Macro-level theories attempt to explain crime within an area or community as the outcome of a wide range of ecological factors, such as poverty and unemployment rates, racial heterogeneity, family structure, and (sub)cultural values and norms. These effects are expected to operate at a contextual level, independently of (or more recently, interacting with) individual-level attributes such as race or sex. Structural conditions like those mentioned above are theorized to contribute to a more or less criminogenic social environment, regardless of the characteristics of individual residents. Currently, a rapidly growing body of macro-level research draws on the social disorganization tradition rooted in the work of Shaw and McKay (1969). This literature primarily focuses on the mechanisms linking structural conditions and crime levels such as social control (Bursik and Grasmick 1993a) and collective efficacy (Morenoff, Sampson, and Raudenbush 2001; Sampson and Groves 1989; Sampson, Raudenbush, and Earls 1997) that were not directly measured in earlier research. Another significant body of work has developed around cultural theories of crime, which propose that structural conditions like poverty promote the development and entrenchment of deviant subcultures, leading to higher levels of crime in these communities (Anderson 1999; Messner 1983; Parker 1989; Wolfgang and Ferracuti 1967).

Within this tradition, one of the longest-standing and highly-debated questions about communities and crime is the relationship between an area's economic conditions and crime rates. There are two conceptualizations of economic conditions commonly used within this body of work. The first, "absolute deprivation," refers to the actual level of resources within an area (e.g. median income, unemployment rate, or mean education). The second, "relative deprivation," refers to the *distribution* of resources across the area's population, such as income inequality. While much of this research focuses only on the relationship between one type of deprivation and crime, contemporary research has begun to compare the importance of absolute and relative deprivation (Blau and Blau 1982; Hipp 2007b; Kelly 2000; Messner 1982; Patterson 1991; Williams 1984). Absolute deprivation, typically measured in terms of poverty levels, has been an historically important factor in the study of crime and criminal behavior (e.g. Quetelet 1835), but a rapidly expanding body of work has shifted the focus to the distribution of resources across a population, or relative deprivation. Each is expected to have independent effects on levels of crime at the macro-level, though the theoretical mechanisms linking them to crime remain unclear. There are a number of factors that complicate this debate, including methodological differences between empirical studies and the considerable overlap between theoretical frameworks used to examine and explain the deprivation/crime relationship, which are considered here and help to inform the current research design and conclusions.

The current study attempts to advance theoretical and methodological discussions about deprivation and crime in several ways. First, unlike previous research that relies on a single-item measure of absolute deprivation, I adopt the approach taken by Sampson and others (Land, McCall, and Cohen 1990; Morenoff, Sampson, and Raudenbush 2001; Sampson, Raudenbush, and Earls 1997) by combining a number of structural indicators of absolute deprivation into a factor-weighted scale, rather than use a single measure like poverty rates. This reduces the multicollinearity between poverty, income inequality, and several other variables that may be driving the inconsistent findings in the research (Kovandzic, Vieraitis, and Yeisley 1998; Land, McCall, and Cohen 1990). By including this variable in analytical models alongside a measure of relative deprivation (here, the Gini index of income inequality), multicollinearity among the predictor variables is diminished and a more accurate picture emerges regarding the theoretical importance of these two mechanisms in the prediction of crime rates.

Second, this research is relatively unique in its methodological approach to the analysis of structural deprivation and crime. Existing research relies almost entirely on cross-sectional designs that are unable to distinguish relationships which are causal from those that are only correlational. The theoretical frameworks commonly used to explain the relationship between structural conditions (including both types of deprivation) and crime rates are inherently dynamic; changes in structural conditions are thought to cause changes in crime outcomes over time. The current research employs a change-score model which taps into the dynamic dimension of the deprivation-crime relationship omitted in previous cross-sectional studies. The few existing studies which do utilize a dynamic model fail to use measures of both absolute and relative deprivation (LaFree, Baumer, and O'Brien 2010; Oh 2005) or use national data to test the relationships (LaFree and Drass 1996; LaFree, Drass, and O'Day 1992) rather than smaller ecological units such as metropolitan areas, counties, or cities.

Finally, the present study examines the relationships between structural conditions, economic deprivation, and crime over time between 1990 and 2000, a period of marked decreases in crime rates across the United States, often referred to as the "crime drop" (Blumstein and Wallman 2006) or the "crime decline" (Zimring 2007). While this phenomenon has generated a significant amount of research, little of it has focused on the relationship between changes in poverty rates or income inequality and the changes in crime rates; much of the focus has been on the power of changes in unemployment rates or wages/median income (Conklin 2003; Zimring 2007) to explain changes in crime levels. However, rather than attempt to explain the crime drop itself, the current study uses the historical circumstances of the crime drop, coupled with divergent trends in poverty and income inequality, as an interesting context to study the relationships over time. Poverty rates during the 1990's decreased nationwide (U.S. Census Bureau 2009, http://www.census.gov/prod/2009pubs/p60-236.pdf), while income inequality was increasing slightly or remaining relatively stable (U.S. Census Bureau 2000, http://www.census.gov/prod/2000pubs/p60-204.pdf). This produces a unique opportunity to examine the different relationships of absolute deprivation and relative deprivation with crime during a period when the gap between these types of deprivation was increasing. The key research question I attempt to answer here is, Does absolute deprivation or relative deprivation more strongly predict crime rates over time? While the current research is unable to distinguish between the different theoretical mechanisms that may be driving the observed relationships, it does allow for conclusions to be drawn about the importance of absolute and relative deprivation for predicting crime rates, and makes a significant contribution to criminological theory by adding to and extending existing research that attempts to refine our understanding of the links between economic conditions and crime.

Poverty and Crime

Within sociological research, poverty has long been considered an important structural condition influencing a number of outcomes, including health, education, and crime, with research on the effects of poverty on crime extending back centuries to the work of Guerry and Quetelet in the early 19th century (Bernard, Snipes, and Gerould 2010). Several macro-level criminological theories developed during the early 20th century also included poverty as an important predictor of crime rates in an area, most notably the work on social disorganization by Shaw and McKay (1969) and anomie (Merton 1938). Poverty is commonly defined as a form of absolute deprivation because of its relationship to the presence or absence of a baseline level of economic resources (Messner 1982), and is operationalized to represent "the lack of some fixed level of material goods that are necessary for survival and minimum well-being" (Bernard, Snipes, and Gerould 2010, p. 105). While different theories assume distinct mechanisms to be at work, the basic relationship remains the same. Areas with higher levels of poverty are expected to have higher rates of crime, because it is the absence of an adequate level of resources (whether income, education, or employment) in an area that drives crime, rather than the maldistribution of resources across the population. For example, conflict theories (Blau and Blau 1982; Blau 1977) posit that individuals living in poverty are likely to resort to crime for two reasons. The first is simply to subsist (Bonger 1969; Cantor and Land

1985); poor individuals commit crimes (e.g. theft) that allow them to meet basic human needs such as food and shelter. This is theoretically similar to rational choice and deterrence theories of crime (Becker 1968; Ehrlich 1973). It is also hypothesized that the frustration and aggression engendered by living in poverty can lead to physical manifestations in the form of crime (Crutchfield 1989; Messner 1983; Turner 1978). Anomie/strain explanations derived from the work of Merton (1938) would likewise predict a positive association between poverty and crime, but for a slightly different reason. The emphasis on success in American culture, particularly economic success, creates a strong drive within individuals to attain economic wealth. Those who fail to attain this goal through socially acceptable means are more likely to resort to deviant or criminal means to achieve it (Merton 1938; Merton 1968; Messner and Rosenfeld 2001). One of the three major components of routine activity theory, the presence of motivated offenders, could also be driven by high poverty concentrations (Carroll and Jackson 1983; Cohen and Felson 1979; Felson and Cohen 1980). Individuals in poverty would be more likely to commit crimes for a variety of reasons related to other theories of crime, such as frustration-aggression, status attainment, or because crime is an acceptable behavior within a subculture (Anderson 1999). Relatedly, because subcultural theories account for the relationship between poverty and crime by hypothesizing that poverty engenders a subculture where criminal behavior is normatively acceptable, these theories are often used to explain regional (i.e. the South vs. the Northeast or West) (Hackney 1969; Rosenfeld 1986; Wolfgang and Ferracuti 1967), racial (i.e. blacks vs. whites) (Anderson 1999; Curtis 1975), and urban/rural (Fischer 1975) differentials in crime rates. Finally, social disorganization theories derived from the work of Shaw and McKay (1969) and ecological theories of communities (e.g. Park, Burgess, and McKenzie 1967) consider poverty to be one factor that contributes to communities being unable to exercise informal social control on its population (Bursik and Grasmick 1993a; Sampson and Groves 1989; Sampson and Wilson 1995; Shihadeh and Steffensmeier 1994). Recent extensions of social disorganization likewise provide several mechanisms explaining how absolute deprivation contributes to community crime. Concentrated poverty can create social isolation between residents of poor neighborhoods and the more conventional middle-class (Krivo and Peterson 1996; Wilson 1987). Collective efficacy, as one process that is theorized to link structural social disorganization to crime outcomes, is also believed to be affected by levels of poverty or absolute deprivation in a community (Sampson, Raudenbush, and Earls 1997). Thus, areas which have higher levels of poverty are viewed as more disorganized, leading to lower levels of collective efficacy (through the weakening of social ties and a diminished capacity of the community to regulate its population's behavior) and thus higher crime.

While these theories and others agree that poverty and crime will be positively correlated at the macro-level, the empirical literature regarding the nature of the neighborhood poverty/crime relationship offers mixed support for this conclusion, with different studies often finding contradictory results. For example, some studies have shown that poverty rates are positively related to violent crime (Decker 1980), assault (Crutchfield, Geerken, and Gove 1982; Harries 1976), property crime (Kelly 2000), burglary (Crutchfield, Geerken, and Gove 1982), homicide (Kposowa, Breault, and Harrison 1995; Loftin and Hill 1974; Messner 1983; Messner and Tardiff 1986a; Williams 1984), and victimization (Sampson 1986; Sampson and Castellano 1982). Others find that poverty rates are not significantly related to crime and victimization (Blau and Blau 1982; Blau 1977; Jacobs 1981), and some researchers have even found an unexpected negative correlation between area poverty or a similar measure of absolute deprivation and a particular category of crime or type of deviance such as homicide (Messner 1982), robbery (Blau and Blau 1982; Crutchfield, Geerken, and Gove 1982), and adolescent substance use (Snedker, Herting, and Walton 2009).

The inconsistent role of poverty rates in explaining crime led some researchers to call for a reconceptualization of “deprivation” (e.g. Messner 1982) based on similar developments in the study of social stratification more generally. This reconsideration has expanded the focus from subsistence-based notions of deprivation, such as poverty, to also including relativist ideas about deprivation where inequality in the distribution of resources (such as income) is a more accurate representation of the true nature of “deprivation.” This idea was quickly adopted in the areas of communities and crime, and intense debate over the roles of absolute and deprivation has been ongoing. However, a review of the inequality and crime literature makes it clear that the relationship between relative deprivation and crime is no clearer than the one between absolute deprivation and crime.

Inequality and Crime

Within the crime/deprivation literature, a growing concern is that absolute measures such as poverty rates fail to fully capture the concept of deprivation. It has been argued that examining the distribution of resources within a population is more relevant to studies of communities and crime (Patterson 1991). Unlike poverty, economic inequality “refers to a comparison between the material level of those who have the least in a society and the material level of other groups in that society” (Bernard, Snipes, and Gerould 2010, p. 105). This body of work posits that it is not a lack of resources, but their unequal distribution across the population, which leads to increased crime at the macro-level. The relationship between income inequality (as a measure of relative deprivation) and crime, like the poverty/crime relationship, can be accounted for by a number of theoretical frameworks, including several previously mentioned above. Conflict theories assert that crime results from a capitalist system engendering large disparities in wealth and income (Bonger 1969). Groups with high levels of social, political, and/or economic capital have the power to defend their values and interests legally, while groups with less power (e.g. racial/ethnic minorities, lower economic classes) must resort to illegitimate means to do so (Bernard, Snipes, and Gerould 2010). Relative deprivation can also lead to an environment of frustration and hostility (Messner and Golden 1992) or attenuate norms of behavior [i.e. create high levels of anomie (Merton 1938) that result in more criminogenic structural conditions (also see Agnew (1999)]. Within routine activity theory (Carroll and Jackson 1983; Cohen and Felson 1979; Felson and Cohen 1980), inequality may inherently increase the presence of 'attractive targets' and 'motivated offenders' because of the close proximity of individuals of disparate economic resources. Social disorganization and related theories of crime predict that inequality may make it more difficult to establish social ties, increasing the 'social distance' between different groups within the population (Blau 1977; Hipp 2007b) and discouraging the establishment of effective informal social control (Morenoff, Sampson, and Raudenbush 2001), thus leading to higher crime rates. Reference group theory, growing out of a more modern conceptualization of strain theory (Agnew 1985; Agnew 1999), contends that individuals will compare themselves to others within their 'reference group' (Harer and Steffensmeier 1992). Criminal behavior results when these individuals, confronted with what they perceive as an inequitable distribution of economic resources, react in such as way as to 'redistribute' such resources or to relieve the frustration that such inequality may cause (Hipp 2007b).

The empirical research testing the relationship between economic inequality and crime parallels the literature on poverty and crime; findings on the direction and strength (or statistical significance) of the relationship between area economic inequality and crime are inconsistent across studies. Typically using a measure of income inequality like the Gini coefficient, some studies have found a significant correlation between inequality and overall crime (Watts and Watts 1981), homicide and assault (Blau and Blau 1982; Rosenfeld 1986), burglary, larceny and robbery (Jacobs 1981), and criminal victimization (Sampson 1985). However, others have found that inequality has no statistically significant relationship with homicide (Bailey 1984; Messner 1982; Messner 1983; Messner and Tardiff 1986a) or robbery (Rosenfeld 1986). Further confounding the issue, there are also contradictory findings in those empirical studies which measure the relationships of poverty and inequality with crime simultaneously. Some research concludes that poverty, but not inequality, is significantly related to crime (Kposowa, Breault, and Harrison 1995; Messner 1982; Patterson 1991). Other results suggest that it is inequality, not poverty, which is important (Blau and Blau 1982; Blau 1977; Jacobs 1981), while others conclude that *both* are significantly related to crime rates (Danziger 1976; Hsieh and Pugh 1993; Loftin and Hill 1974).

In summary, a lack of consistent results across studies examining the associations of either absolute or relative deprivation (or both) with crime rates makes it difficult to draw general conclusions about the nature of the relationship between deprivation and crime within communities. Research in this vein has begun to consider how methodological differences across studies may contribute to this diverse set of findings, with four primary methodological concerns emerging as major factors that influence observed relationships between poverty rates, economic inequality, and crime rates.

Methodological Concerns

Consistent expectations of positive associations between absolute deprivation, relative deprivation, and crime across several theoretical frameworks has led researchers to conclude that the inconsistent empirical findings within the literature are not necessarily due to inherently flawed theories of crime, but are instead the result of methodological inconsistencies and shortcomings. Recent studies (Kovandzic, Vieraitis, and Yeisley 1998; Land, McCall, and Cohen 1990) have pointed to four major methodological issues that contribute to the equivocal findings in the literature: (1) the level of aggregation used (e.g. states, counties, SMSA's), (2) the analytic sample, (3) the variables included in the model as well as multicollinearity among them, and (4) model specification.

First, it is unclear which level of aggregation is most appropriate to study macro-level relationships between deprivation and crime. Researchers in this literature utilize many different levels of geographic aggregation, including police districts, neighborhoods, census tracts, cities, counties, metropolitan areas, states, and entire nations [see Hsieh and Pugh (1993) and Britt (1991) for examples]. This variety results from both the difficulty in obtaining data at different levels, as well as scholarly disagreements over the proper level of measurement implied by criminological theory (Hipp 2007b; Kposowa, Breault, and Harrison 1995; Messner and Tardiff 1986a; Patterson 1991). A current debate on reference groups exemplifies this issue; what level of aggregation accurately captures the true nature of a given individual's or group's frame of reference when considering economic conditions (Harer and Steffensmeier 1992; Hipp 2007b; Wang and Arnold 2008)? It is also possible that the mechanisms driving these relationships will vary depending on the level of aggregation used, so that studies using two different levels of measurement with contradictory findings may both be correct. However, Land et.al. point out that general structural theories of crime "should be capable of accommodating *all* these levels of analysis" (1990, p. 933). Moreover, existing studies typically focus on only one level of analysis (though see Land, McCall, and Cohen 1990 for a notable exception), so that assessing the relationships between absolute and relative deprivation and crime at multiple levels of aggregation requires comparing separate studies which often vary in variable selection/operationalization, sampling frameworks, time periods, and analytic methods. Each of these differences can independently influence results and make it difficult (if not impossible) to account for the direct influence of the level of aggregation on the findings. There is little consensus on a clear solution to the aggregation problem. Rather than deal directly with this issue, most researchers simply make a case for why the mechanisms of interest in a given study should operate most strongly at the level of aggregation they have chosen to analyze. There has been some recent work attempting to account for the effects of aggregation on findings, but is generally limited to comparisons of models across levels (Hipp 2007a; Land, McCall, and Cohen 1990) or multi-level models including individual-level variables nested within a single larger level of analysis (Sampson, Raudenbush, and Earls 1997), which are still vulnerable to criticism aimed at the choice of the larger aggregation. The aggregation problem requires research in this area to perform a balancing act – information is more readily available at larger aggregates, and for more areas (making results generalizable across a larger population), but its use risks masking significant intra-unit variation on important variables. The choice of metropolitan counties as the unit of analysis in the current study is subject to this same issue, and primarily methodologically driven; it is the smallest aggregation for which national data is publicly available and results can be generalized to the entire country, while avoiding the masking problem inherent in the use of entire SMSA's and states.

Second, even when studies use identical levels of aggregation, their analytic samples often vary considerably. For example, studies focusing on smaller levels of aggregation, such as census tracts or neighborhoods (however defined), typically limit their samples to areas within a single larger unit such as a city (Krivo and Peterson 1996; Messner and Tardiff 1986a; Morenoff, Sampson, and Raudenbush 2001; Sampson, Raudenbush, and Earls 1997). Among studies which sample small units from more than one large area (Hipp 2007b; Patterson 1991), there are still important differences, such as the aggregate level of the larger area (e.g. neighborhoods within cities vs. neighborhoods within SMSA's). There are also artificial limits placed on samples of larger units of analysis like cities, counties, and SMSA's. Though Land et.al. (1990) point out that there is usually no theoretical reason to constrain analyses to areas with large populations, it is quite common to find studies employing a minimum population criterion when selecting the sample. Moreover, this criterion can vary across studies [e.g. cities of 100,000 (Krivo and Peterson 2000; Oh 2005; Shihadeh and Steffensmeier 1994) or 25,000 (Stolzenberg, Eitle, and D'Alessio 2006), SMSA's of 250,000 (Blau and Blau 1982; Williams 1984) or all metropolitan areas (Land, McCall, and Cohen 1990; Messner 1982)].

The use of disparate analytic samples based on different sampling methodologies weakens the ability of scholars and researchers to compare results across studies which ostensibly use the same level of aggregation. The generalizability of results may be limited to extremely large cities or metropolitan areas rather than be representative of the relationships for all cities or SMSA's. The current study avoids this problem by using all metropolitan area components (typically counties, though several unincorporated cities are also included) for which data is available in 1990 and 2000. In this way, the results are generalizable to all metropolitan area components within the U.S., not just the oldest or the largest. The results can also be used as a benchmark for studies which do limit their sample based on component size or region. The relationships found in this study can be treated as baselines against which regional or size differences can be judged (e.g. is the relationship of racial heterogeneity and crime in the South different than for all U.S. metropolitan counties?)

Third, studies across the deprivation and crime literature remain inconsistent when selecting variables to include or omit from statistical models. Depending on the theoretical framing of a given study, many different variables are used as control or mediating variables. A recent meta-analysis of macro-level studies of crime by Pratt and Cullen (2005) lists over 30 variables that are used to test existing theories. This makes comparisons across studies more difficult in the same way that it is difficult to compare studies using different geographical aggregations. There are several variables, however, that are widely used across theoretical frameworks in the deprivation and crime literature, such as poverty rates, income inequality, unemployment rates, percent nonwhite or racial heterogeneity, female-headed households, urbanization, home-ownership, housing vacancy rates, and education. Many of the theories informing research on absolute and relative deprivation and crime share a common opinion on the importance of these variables, while continuing to disagree on the mechanisms that link them to crime.

Additionally, multicollinearity is a significant methodological issue related to the selection and operationalization of variables used in a given statistical model. When several variables within a model are highly intercorrelated, multicollinearity can lead to several problems, including large changes in regression coefficients when a variable is entered or removed from the model, large confidence intervals and nonsignificant test coefficients, and relationships in a direction opposite of what it theoretically predicted (Land, McCall, and Cohen 1990). This leads to inconsistent findings across studies using different samples and levels of aggregation. A particularly worrisome problem is the “partialing fallacy” (Gordon 1968). It is possible that of several highly correlated independent variables, the one having the strongest correlation with the dependent variable has all of the explained variance attributed to it, though its correlation with the dependent variable may only be slightly larger than the other collinear independent variables (Land, McCall, and Cohen 1990). This seems particularly problematic in studies of poverty and crime when other factors such as unemployment, female-headed households, and education are included in the models, given that these variables are strongly related both empirically and conceptually as facets of absolute deprivation (Land, McCall, and Cohen 1990; Loftin and Hill 1974; Sampson, Raudenbush, and Earls 1997). The current study uses a factor-weighted measure of absolute deprivation that combines these highly correlated variables. This reduces the influence of highly collinear variables on the measure of absolute deprivation.

The final problem encountered in the existing deprivation and crime literature is that most studies fail to focus on the inherently dynamic nature of the relationship between economic conditions and crime at the macro-level. Theories of crime at the individual-level often focus on the propensity of an individual to commit criminal acts or be victimized by another (Pratt and Cullen 2005) based on characteristics of his or her education, race, income, etc. At the macro-level, however, the theoretical focus typically rests on how key community features (in this case, economic conditions) affect crime rates through the relationship between structural conditions and mechanisms such as social disorganization or collective efficacy (Bursik and Grasmick 1993a; Morenoff, Sampson, and Raudenbush 2001; Sampson and Groves 1989) or the frustration/strain experienced by individuals lacking material resources (Crutchfield 1989; Merton 1938; Messner 1983; Messner and Golden 1992). While these theoretical frameworks certainly predict static, between-area differences, they are also implicitly dynamic, suggesting that within-community changes in structural conditions lead to changes in crime rates (Bursik 1986). For example, if relative deprivation is positively related to crime through the coexistence of motivated offenders and attractive targets, reductions in relative deprivation should decrease the population of motivated offenders (if poorer residents leave or increase their incomes) or attractive targets (if wealthier residents leave or lower their incomes) and thus result in less crime. It is for this reason that the relationships between structural conditions and crime rates should be examined longitudinally. However, there is a lack of research which actually employs changes in the community over time to model these relationships. There are a number of studies that examine the deprivation/crime relationship for multiple time periods [e.g. Sampson and Groves (1989); Bursik and Grasmick (1993a);

Shihadeh and Ousey (1998)], but most analyses are limited to models that can only capture the relationships in cross-section, which neglects the dynamic nature of the processes theorized to be at work. One method that has been used to control for previous levels of a given variable is a time-lagged model, where a standard regression model includes a prior measure of the variable of interest (such as homicide rates or violent crime rates) (Choe 2008). However, time-lag models only control for previous levels of the dependent variable and do not address the problems of unobserved heterogeneity between units well (Allison 1990). An alternative method that has rarely been employed [see Oh (2005) for an exception] is a change-score model, which measures change in the level of the dependent variable and regresses it on changes in the levels of the predictor variables of interest. The current study employs a similar change-score model to examine the association of *changes* in structural conditions with *changes* in levels of crime across areas between 1990 and 2000. It is expected that the relationships between change in structural conditions and changes in crime will mirror the relationships found in the cross-sectional analyses.

Moreover, cross-sectional models can only rarely estimate the causal effect of a structural covariate such as income inequality on crime rates. An experimental or quasi-experimental design is typically necessary, where a key independent variable would be randomly assigned to a homogenous sample; such a design assumes that any unmeasured heterogeneity between units is controlled through randomization. However, this research design is difficult to employ in sociological and criminological research, particularly in macro-level studies (see the "Moving to Opportunity" program for an exception; Katz, Kling, and Liebman 2001). Unobserved heterogeneity and omitted variable bias remains a potential problem in existing research on deprivation and crime rates at the macro-level. Dynamic models like change-score analysis control for time-stable heterogeneity between units and remove the potentially confounding effects of unmeasured, time-stable variables from the statistical model. By analyzing data from the decennial years “bookending” the crime decline in the 1990s, I capitalize on the relatively large variations in crime rates over time. Additionally, incorporating a temporal dimension into the models helps distinguish between the relationships of absolute and relative deprivation with crime, given the previously discussed increasing gap between absolute and relative deprivation levels over the same period. Caution is warranted in making causal inferences based on these models, however. Change-score models, like cross-sectional OLS models, are subject to omitted variable bias when unmeasured sources of heterogeneity between units are time-variant.

It is important to note that a number of scholars have pointed out that it is often empirically difficult (if not impossible) to determine which of several theoretical mechanisms are driving the poverty/crime or inequality/crime relationship, given that there is considerable overlap among theories regarding which structural features of communities are considered to be important. Much of the existing empirical literature on deprivation and crime at the macro-level, rather than measuring the mechanisms hypothesized to intervene between structural features of the community and crime outcomes, instead assumes the presence of such mediating factors as collective efficacy, anomie/strain, or motivated offenders. Previous research has noted the difficulty in collecting data on the intervening processes (Pratt and Cullen 2005), given that in most cases, structural features at the macro-level are hypothesized to affect individual-level processes or responses and lead to changes in crime indirectly.

Gathering data on both levels at once is time-consuming, expensive, and otherwise hard to gather. Several studies have found links between absolute and/or relative deprivation and measures of the theorized mediating processes such as collective efficacy (Morenoff, Sampson, and Raudenbush 2001), social disorganization (Sampson and Groves 1989), or social capital (Kennedy, Kawachi, Prothrow-Stith, Lochner, and Gupta 1998). However, in studies that measure the intervening processes, the sampling design and analytic sample make it challenging to generalize to a larger population. It is not the aim of the present study to critically test a specific criminological theory or set of theories; it is beyond the scope of this research to measure and test the mechanisms linking structural conditions and crime. Rather, the goal is to refine our understanding of the relationships between absolute and relative deprivation and crime at the aggregate level.

Each of the preceding methodological concerns is addressed in the current research. While issues of aggregation and analytic sampling are not the primary methodological concerns of this study, an argument is made for the use of counties within metropolitan areas as an appropriate level of aggregation. Furthermore, all possible counties with available data on structural conditions and crime rates are included; results based on this sample are more generalizable than previous studies which only used large cities or metropolitan areas (e.g. 100,000 or 250,000 people). The major methodological contribution of this research focuses on the issues of multicollinearity related to variable selection and the use of a dynamic model to examine inherently dynamic processes and control for unmeasured time-stable heterogeneity between units. The following section discusses how the current study addresses each of these issues and describes the research design employed here.

Data and Methodology

Sample

The current study uses counties (and a number of unincorporated cities where appropriate) defined as components of standard metropolitan statistical areas (SMSA's) in both the 1990 and 2000 U.S. decennial census and for which crime data was available on seven Part I crimes as defined by the Federal Bureau of Investigation (FBI) and compiled in the annual Uniform Crime Report (UCR) published by the FBI. Counties were chosen as the primary unit of analysis in this study for two reasons. It has been argued that metropolitan areas are a more appropriate level of analysis (Blau and Blau 1982; Messner 1982; Williams 1984) than states because states are "arbitrary statistical aggregations that include vastly different ecological units" (Kovandzic, Vieraitis, and Yeisley 1998). Using data aggregated to the state level hides a significant amount of within-unit variation on both crime and sociodemographic characteristics (Land, McCall, and Cohen 1990). This same criticism, however, has been aimed at the use of SMSA's as the unit of analysis. Bailey (1984) and others (Kovandzic, Vieraitis, and Yeisley 1998; Parker 1989) have argued that the use of cities is more appropriate because SMSA's commonly include areas that are quite different in terms of socioeconomic, demographic, and crime level characteristics. For example, densely populated central-city areas are included alongside less densely populated suburban areas and at times, sparsely populated rural areas. Others have argued that counties, rather than cities, should be used (Kposowa, Breault, and Harrison 1995), because there is too little variation within cities and other large urban areas; limited variability can contribute to multicollinearity among variables and distort the results of statistical analyses. Furthermore, by focusing on cities, we limit the generalizability of the inferences we can draw about structural conditions and crime to urban areas and reinforce "the view that it is the city…which is pathological" (Kposowa, Breault, and Harrison 1995, p. 87).

While this ongoing debate in the literature is beyond the scope of the current research to resolve, I agree with the conceptual arguments made by Kposowa and colleagues (1995) Using entire SMSA's masks considerable within-unit variation in structural composition while using only cities focuses too narrowly on highly urban areas which also tend to have little variation on related structural variables such as poverty rates, unemployment, and education. Furthermore, many of the metropolitan areas defined by the U.S. Census are comprised of only a single county component. This means that the definition of the "county" and the "metropolitan area" are identical (e.g. the State College, PA SMSA is the same geographical unit as Centre County); previous studies that include single-county SMSA's alongside multi-component SMSA's are essentially comparing two conceptually distinct aggregations. The current sample contains 158 single-county SMSA's and 520 multi-component SMSA's, suggesting that previous research has overlooked this important distinction. Conclusions about metropolitan area-level relationships may be flawed since there could be differences between component- and SMSA-level relationships. I address this distinction in the current study by limiting my conclusions to the component-level relationships between structural characteristics and crime, rather than characterize the relationships as something that occurs in metropolitan areas generally, conceptually and empirically distinguishing these two levels of aggregation.

Using the smaller aggregate of county components within SMSA's is useful for a methodologically practical reason as well – it substantially increases the size of the analytic sample and thus adds to the statistical power of the regression models. This is a particular concern in studies of absolute and relative deprivation, given the strong correlations commonly observed between independent variables such as poverty and unemployment rates. While high correlations do not invariably lead to inefficient estimates, increasing the size of the sample reduces the size of standard errors associated with multicollinearity and makes Type II errors less likely (Allison 1999; Kposowa, Breault, and Harrison 1995). Since one of the methodological focuses of the current study is the reduction of multicollinearity and its negative impacts on the estimation of the relationships of absolute and relative deprivation with crime, using the components of metropolitan areas is warranted.

Data from the census was used to operationalize a number of structural covariates common to macro-level research on crime as well as the key independent variables of absolute and relative deprivation, while multiple years of UCR data were used to construct measures of the average rates of crime for the years 1989-1991 and 1999-2001. All counties and independent cities defined as components of SMSA’s by the Census Bureau in both 1990 and 2000 were selected for the sample. New England states were excluded from this study, as metropolitan areas in this region rely on substantively different definitions of components and are not easily compared to metropolitan area components in other regions of the U.S. Components lacking at least two years of UCR data for each of the two time periods examined are also excluded because average crime rates cannot be calculated. Finally, the Cook’s D statistic was used to test for the presence of highly influential cases on model estimations; there were none. The final sample size is 678 components, including 650 counties and 28 independent cities. For simplicity these components will from this point simply be referred to as counties, given that there are comparatively few independent cities in the sample. Appendix A contains a complete list of the units included in the sample.

Dependent Variables

Table 1 lists descriptive statistics for the dependent, independent, and control variables used in these analyses for 1990, 2000 and the changes between the two decennial periods. Crime data for this study was obtained from the Federal Bureau of Investigation's (FBI's) annual Uniform Crime Reports (U.S. Department of Justice 1989; 1990; 1991; 1999; 2000; 2001).

County-level crime data was not available directly from the FBI; however, the Inter-university Consortium for Political and Social Research (ICPSR) has compiled county-level statistics based on original UCR data. Crime rates were calculated as the number of offenses reported to the police per 100,000 population, based on the average number of crimes over a three-year period (1989-1991 or 1999-2001). Using three-year (or in several cases, two-year) averages encompassing the census years makes it possible to minimize error produced by yearly fluctuations in crime rates (particularly for rare crimes such as homicide) and also increases the likelihood of having a sufficient number of reported offenses to construct reliable rates (Kovandzic, Vieraitis, and Yeisley 1998; Krivo and Peterson 1996; Krivo and Peterson 2000; Messner and Golden 1992; Morenoff, Sampson, and Raudenbush 2001).

Table 1. Descriptive Statistics (N = 678)

	1990				2000				Change-score (1990-2000)			
Dependent Variables	Mean	(SD)	Min.	Max.	Mean	(SD)	Min.	Max.	Mean	(SD)	Min.	Max.
Total offenses[a]	8.323	(0.63)	4.68	9.64	8.081	(0.59)	3.67	9.58	-1114.962	(1496.92)	-11219.21	4141.82
Violent offenses[a]	5.848	(0.90)	2.29	8.16	5.685	(0.80)	2.19	7.71	-105.637	(251.40)	-1675.83	609.72
Property offenses[a]	8.223	(0.62)	4.60	9.43	7.975	(0.59)	3.45	9.41	-1009.929	(1330.46)	-9543.17	3705.71
Homicide offenses[a]	1.727	(0.76)	0.00	4.35	1.422	(0.71)	0.00	3.75	-2.205	(3.82)	-34.75	15.36
Independent and Control Variables												
Absolute deprivation	0	(1.00)	-2.26	4.12	0	(1.00)	-2.23	5.58	0	(0.40)	-1.23	5.22
Relative deprivation	0.403	(0.03)	0.27	0.52	0.402	(0.03)	0.31	0.50	-0.001	(0.01)	-0.05	0.04
Total population[ab]	11.779	(1.13)	8.75	16.00	11.930	(1.12)	8.84	16.07	37.501	(76.70)	-84.86	950.05
Urbanization	0.671	(0.26)	0.00	1.00	0.728	(0.23)	0.00	1.00	0.057	(0.09)	-0.17	0.59
Young adults	0.109	(0.04)	0.05	0.48	0.098	(0.04)	0.04	0.46	-0.011	(0.01)	-0.08	0.10
Vacant housing	0.085	(0.05)	0.03	0.56	0.077	(0.04)	0.02	0.54	-0.008	(0.02)	-0.11	0.05
Owner-occupied housing	0.686	(0.10)	0.18	0.88	0.703	(0.10)	0.20	0.89	0.018	(0.02)	-0.04	0.10
Residential stability	0.531	(0.08)	0.13	0.73	0.542	(0.07)	0.15	0.74	0.010	(0.03)	-0.12	0.19
Hispanic	0.051	(0.10)	0.00	0.94	0.075	(0.12)	0.00	0.94	0.023	(0.03)	-0.01	0.17
Foreign-born	0.041	(0.05)	0.00	0.36	0.062	(0.07)	0.00	0.51	0.021	(0.02)	-0.01	0.12
Racial heterogeneity	0.379	(0.21)	0.02	1.00	0.462	(0.22)	0.06	1.00	0.083	(0.05)	-0.12	0.37

[a] Transformed using the natural log in 1990 and 2000; untransformed in the change-score

[b] Total population in 1000's in the change-score descriptives

Based on offense data available from the FBI, I construct four crime rate outcomes. *Total crime rate* includes seven Part I index crimes used in the UCR reporting program: homicide, rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft. Crimes were also divided into the *violent crime rate* (which includes homicide, rape, robbery, and aggravated assault) and the *property crime rate* (which includes burglary, larceny, and motor vehicle theft) to examine possible differences between the two types of crime. Finally, the *homicide rate* was constructed so the results of the current research could be compared to the large number of previous studies of structural deprivation and crime rates focusing on only homicide (e.g. Krivo and Peterson 2000; Morenoff, Sampson, and Raudenbush 2001; Parker 1989; Wang and Arnold 2008). The definitions of the seven Part I index crimes used to construct the dependent variables are listed in Appendix B.

For the cross-sectional analyses, each of the four crime rate variables was transformed using the natural log (ln) to normalize the distribution, due to the "floor effect" (a unit cannot have fewer than zero reported offenses) and the tendency for crime rates to cluster at or near zero. The distributions for all four outcomes were highly skewed in a positive direction in both 1990 and 2000. In the change-score model, no transformation of the crime rates was necessary. The differencing procedure used to calculate the change-score variables normalizes their distributions (i.e. the distribution of the *changes* in crime rates approaches normality, whereas the distribution of crime rates at a single point in time does not), so that crime variables in the change score model are measured as actual changes in number of crimes reported per 100, 000 population (e.g. there were on average over 1,100 fewer total index crimes per 100,000 people reported to the police in 2000 than in 1990). Histograms displayed in Appendix C demonstrate this principle by comparing the untransformed distribution of total crime change with the untransformed distribution of total crime in the 1990 and 2000 cross-sections.

Independent Variables

Decennial census data was used to construct measures of county-level structural and demographic composition in 1990 and 2000. The principal independent variables of interest, absolute deprivation and relative deprivation, were operationalized to reflect average levels of economic resources and the distribution of those resources across the population, respectively. Many previous studies have used a single measure of absolute deprivation, typically the poverty rate (Kawachi, Kennedy, and Wilkinson 1999; Kennedy et al. 1998; Kovandzic, Vieraitis, and Yeisley 1998; Messner 1982; Williams 1984) or the rate of households or families falling below a given level of income (Krivo and Peterson 1996; Messner and Tardiff 1986a). Other measures of absolute deprivation have been used, including median family income, education levels, and unemployment rates (Kovandzic, Vieraitis, and Yeisley 1998). As previously noted, however, there are strong correlations between poverty rates and other variables commonly included as control variables, such as education levels, unemployment rates, and the number of female-headed households. Such correlations likely lead to inflated standard errors and partialing effects that distort results. Contemporary work within the social disorganization and collective efficacy framework (Morenoff, Sampson, and Raudenbush 2001; Sampson, Raudenbush, and Earls 1997) often uses a "concentrated disadvantage" measure, or an index which combines several highly interrelated variables loading on a single underlying factor. There is also precedent for using such an index measure in analyses of absolute deprivation. Loftin and Hill (1974) created a "structural poverty" index combining a measure of the low income population (percentage of families with incomes below $1000) with measures of family structure, education, and health conditions (see also Huff-Corzine, Corzine, and Moore 1986). The current study adopts this strategy in an attempt to minimize the effects of multicollinearity on estimates of the relationship between absolute deprivation and crime rates. While such a strategy makes it impossible to identify the unique association of poverty with crime (Messner 1982), previous research suggests that the concept of absolute deprivation extends beyond poverty. Because prior studies indicate that there is a single latent mechanism linking several structural variables, I created a measure of *absolute deprivation* that is an index of the percentage of households living in poverty, the percentage of female-headed households, the percentage of residents with a high-school degree, and the percentage of persons in the workforce who are unemployed. This index is constructed using rotated principal-component factor-analysis. Consistent with previous research using a similar index measure, the four variables displayed in Table 2 are strongly correlated and load on a single factor in both 1990 and 2000. Following the factor analysis, I generated predicted values of absolute deprivation for each county; because the index is standardized to correct for the means and standard deviations of each of the four component variables, the resulting variable has a mean of zero and a standard deviation of one.

Table 2. Rotated Factor Analysis of Absolute Deprivation (1990 & 2000)

	Factor loading	
Variable	1990	2000
Below poverty	0.925	0.934
Female-headed households	0.738	0.801
High-school graduates	-0.692	-0.720
Unemployed	0.851	0.751

Several methods of measuring relative deprivation have been employed in the past, including the Robin Hood Index of income proportions by decile (Kawachi, Kennedy, and Wilkinson 1999) and the ratio of the percentage of total income received by the top 20% of families or household to the percentage received by the bottom 20% (Kovandzic, Vieraitis, and Yeisley 1998). The latter is similar to the index created by Massey (2001) to measure income concentrated at the extremes (ICE). By far the most common measure of relative deprivation or inequality, however, is the Gini index of income inequality. Used here as a measure of *relative deprivation*, the Gini is a standardized index with values ranging from 0 (perfect equality; every family or household has the same income) to 1 (perfect inequality; one family/household has all the income, the other have none). The decennial census provides annual household income in 25 intervals in 1990 and 16 intervals in 2000. These intervals were combined, when necessary, so that the intervals were identical across census years. Each interval was recoded to its midpoint (e.g. “$1,000 to $1,500” into “$1,250”) and weighted by the number of households in the county falling into each interval. The Gini Index was then calculated in STATA for each of the counties in the sample for 1990 and 2000; the equation used by STATA can be found in Appendix D.

As the Gini is the most common measure of relative deprivation, it is easier to compare the present results to earlier work. In addition, the Gini satisfies the principle of scale invariance, meaning that multiplying all the incomes in a given population by a constant leaves the Gini coefficient unchanged, as well as the principle of transfers, where transfers of income from a poorer individual to a richer one will increase the value of the coefficient (Allison 1978). However, Gini estimates calculated on grouped data (such as the income intervals from the

Census) can underestimate income inequality, due to the difficulty in establishing an accurate income midpoint for the uppermost category of the distribution. Guided by previous research, the valued assigned to the income midpoint used in this analysis for the interval of "$150,000 or more" was 200,000. This value is somewhat arbitrary; using a larger value would increase the Gini coefficient for every county in the sample (assuming there was at least one household that fell into this interval). While this may make it more difficult to find a statistically significant relationship between income inequality (as the measure of relative deprivation) and crime rates, if a significant relationship *is* observed, this implies that the true relationship may actually be stronger given the conservative test employed here.

It is also possible that using a single-item measure of relative deprivation alongside a multiple-item measure of absolute deprivation "stacks the deck" in favor of finding a stronger relationship between crime and absolute deprivation. While the factor analysis above and previous research supports the use of a factor measure based on the presence of a strong underlying construct, it is possible that this is the case, and the results of the analyses will be interpreted with this in mind. Furthermore, a supplemental analysis of homicide in 1990 included poverty rates, rather than the multi-item factor measure of absolute deprivation, in the models. This analysis shows that the relationship between poverty and homicide generally parallels the relationship between the factor measure of absolute deprivation and homicide, indicating that the use of the factor measure does not substantially change the conclusions drawn about the relationship between absolute deprivation and homicide. In fact, this supplemental analysis suggests that multicollinearity is less problematic in the factor-measure models. Identical models of poverty and the other crime outcomes (not displayed) evidence similar patterns. The poverty-homicide models and a brief discussion are included in Appendix E.

Control Variables

While the focus of the current study is on the importance of absolute and relative deprivation, a number of control variables are included in order to avoid model specification error (Messner 1983; Pratt and Cullen 2005) and minimize the possibility that the relationships between deprivation and crime are spurious. These variables are included in the full models alongside the key independent variables of absolute and relative deprivation, guided by a review of existing studies on deprivation and crime rates. Each of these variables is commonly used in previous analyses to control for structural conditions besides deprivation (Hipp 2007b; Kovandzic, Vieraitis, and Yeisley 1998; Krivo and Peterson 1996; Pratt and Cullen 2005). Like the deprivation measures discussed above, the current research design makes it impossible to distinguish between the theoretical mechanisms that link structural conditions to the levels of crime that occur in an area; several theoretical explanations could be applied to each of these relationships. All of these measures are constructed from 1990 and 2000 decennial census data.

The *total population* of a county is used to control for differences in absolute population size across the sample. This variable was highly skewed and transformed using the natural log (ln) for the cross-sectional analyses; in the change-score model, the distribution is normalized through the difference procedure and no transformation was necessary. *Urbanization* is the proportion of a county's population that lives within an urban area as defined by the U.S. Census; previous research suggests that urban areas suffer from disproportionate levels of crime for several reasons, including increased contact between attractive targets with motivated offenders (Cohen and Felson 1979), deviant subcultures that develop within urban areas (Fischer 1975), and weaker social ties and social organization (Sampson and Groves 1989). Past research has noted both higher propensities for crime to be committed by and against teenagers and young adults (Land, McCall, and Cohen 1990), so *young adults* is included in the model to represent the proportion of a county's population that falls in the crime-prone age range of 18 to 24 years old. Three measures of population stability are included in the model, given that they are commonly theorized to affect levels of social control and collective efficacy (Sampson and Groves 1989; Sampson, Raudenbush, and Earls 1997), community attachment (Krivo and Peterson 1996), or the presence or absence of capable guardians (Cohen and Felson 1979); they generally operate as proxy measures for the attractiveness of a given community. *Vacant housing* is the proportion of all dwelling units that are vacant for the majority of the year and suggests less attractive areas. Inversely, *owner-occupied housing* indicates more commitment to remain in an area (given the financial investment involved), while *residential stability* measures population turnover and is the proportion of a county's population that lived in the same location five years previous to the census.

Several measures of racial and ethnic composition are also included in the models. *Hispanic,* the proportion of the population that self-reports being of Hispanic or Latino origin, and *foreign-born,* the proportion of the population that were not U.S. citizens at birth, have been used as measures of immigrant concentration (Bursik 1986; Morenoff, Sampson, and Raudenbush 2001; Sampson, Raudenbush, and Earls 1997), typically in studies using a social disorganization/collective efficacy framework. Finally, an entropy measure of *racial heterogeneity* was calculated to capture the racial/ethnic diversity of a given county. A three-group (white, black, and other) index score calculated for each county (Reardon and Firebaugh 2002), the entropy index (E) is used to reflect the proportion of people in a given race/ethnicity group controlling for the total number of racial/ethnic groups. The equation used to calculate E is included in Appendix D; calculated scores were divided by the maximum value (1.089) to impose a minimum value of zero (when the county is composed entirely of one race/ethnic group) and a maximum value of one (when all three groups are equally represented). Racial heterogeneity may negatively impact social disorganization (Shaw and McKay 1969) and could also be a source of conflict among individuals within an area (Sellin 1938). Definitions and descriptions of each of the independent and control variables can be found in Appendix D.

Analytic Strategy

The current study explores the relationships between county-level absolute and relative deprivation and crime rates in an attempt to answer several questions. The first is the most essential – what *are* the relationships between absolute and relative deprivation and crime rates, controlling for a variety of other structural conditions? Furthermore, are both types of deprivation significantly related to crime rates when included together in the models, and does one type have a substantially stronger relationship with crime than the other? Are the relationships the same at two distinct points in time? Finally, are the cross-sectional relationships the same as the longitudinal relationships? Using selected metropolitan components, two statistical methodologies are employed to examine these relationships: traditional cross-sectional OLS regressions of two time points (1990 and 2000) and change-score regressions that estimate the relationships between changes in levels of the independent variables with changes in the levels of crime between 1990 and 2000.

I first estimate four cross-sectional OLS models for each of the crime outcomes (total crime, property offenses, violent offenses, and homicide). In Model 1, the crime outcome is first regressed on the factor measure of absolute deprivation alone. Secondly, in Model 2 the crime outcome is regressed on only the measure of relative deprivation (the Gini coefficient of income inequality). Model 3 then estimates the relationships of both absolute and relative deprivation with the crime outcome, excluding the other structural factors. Finally, in Model 4 the full model is presented which estimates the relationships between both types of deprivation and crime, controlling for the effects of the other structural variables. The mathematical notation of the final model is:

$$\text{Crime rates} = \alpha + \beta_1(\text{absolute deprivation}) + \beta_2(\text{relative deprivation}) + \beta_3(\text{population}) + \beta_4(\text{urbanization}) + \beta_5(\text{young adults}) + \beta_6(\text{vacant housing}) + \beta_7(\text{owner-occupied housing}) + \beta_8(\text{residential stability}) + \beta_9(\text{Hispanic}) + \beta_{10}(\text{foreign-born}) + \beta_{11}(\text{racial heterogeneity}) + \varepsilon$$

The notation indicates that the effect of each covariate is assumed to be stable across units and over time. This means that estimates generated using this model are based on between-unit variance and any conclusions are based on deviations from sample-level means of a given variable. This also implies that unmeasured heterogeneity between units (such as differences in crime-reporting procedures to the UCR program) could be biasing the estimates if there are unit-variant effects that are not controlled for in the model.

In addition to the cross-sectional analyses, I also estimate four change-score models for each crime outcome. This second set of analyses uses change-scores created for each covariate and regresses the *change* in crime rates on the *changes* in the predictors in a standard OLS model. Change is calculated as the difference between the 2000 and 1990 values for each variable; negative change values indicate decreases over time (e.g. less total crime reported in

2000) and positive values indicate increases (e.g. more racial heterogeneity within counties in 2000). Also known as “first-difference” models, one type of the more general fixed-effects method (Firebaugh 2008), change-score models replace the restrictive regression assumption that measured and unmeasured causes of the outcome are uncorrelated with the more realistic assumption that the levels and effects of unmeasured causes are invariant. Allison (1990) showed that change score estimates were robust to issues of measurement error, and argued that when their use is theoretically appropriate, change scores increase the ability to make causal inferences from nonexperimental data (also see Halaby 2004).

The regression models now estimate the relationships between changes in a predictor variable with the changes in crime reported to the police, net of changes in the other covariates included in the model. The notation for this model is:

$$\Delta\text{Crime} = \alpha + \beta_1(\Delta\text{ absolute deprivation}) + \beta_2(\Delta\text{ relative deprivation}) + \beta_3(\Delta\text{ population}) + \beta_4(\Delta\text{ urbanization}) + \beta_5(\Delta\text{ young adults}) + \beta_6(\Delta\text{ vacant housing}) + \beta_7(\Delta\text{ owner-occupied housing}) + \beta_8(\Delta\text{residential stability}) + \beta_9(\Delta\text{ Hispanic}) + \beta_{10}(\Delta\text{ foreign-born}) + \beta_{11}(\Delta\text{ racial heterogeneity}) + \Delta\varepsilon$$

The change-score model, like cross-sectional OLS regression models, assumes that the effects of the changes are stable across units. As a result, the coefficients produced are based on between-unit variance, or a given county’s deviation from the sample mean change of a given variable. While change-score models cannot isolate the effects of within-unit change on crime (a third time point would be necessary to calculate a unit-level average), a major advantage is they eliminate the effects of unobserved between-unit heterogeneity as a source of bias, assuming that these differences are time-invariant. For example, these models control for geographic location without explicitly including it in the model because if County “A” is in the South in 1990, it remains so in 2000. Time-stable crime-reporting procedures that vary across units are likewise eliminated as potentially biasing, eliminating a significant source of error in the use of UCR data.

Results

Crime and Deprivation in 1990

Tables 3 through 6 present OLS regression results for models of the natural log of total offenses, violent and property offenses, and homicides reported to the police in 1990. For each outcome, I analyzed the relationships in four steps. I included absolute deprivation and relative deprivation in the models separately in Models 1 and 2, respectively, before examining their relationships with crime concurrently in Model 3. I then addressed potential sources of spuriousness by adding the set of theoretically relevant controls in Model 4. Overall, there are several patterns that emerge from the 1990 analyses that are fairly consistent across all of the outcomes. First, the associations of both absolute deprivation and relative deprivation with crime are always significant and in a theoretically expected positive direction when each is used as the sole predictor of the outcome, explaining roughly a tenth to a third of the variance in crime levels. Secondly, both types of deprivation usually continue to have statistically significant relationships to crime when included together in Model 3. It should be noted that strong correlations between the two measures of deprivation ($r = .76$, $p < .01$) could indicate that collinearity may be driving the inconsistent estimates in Model 3 across the four crime outcomes. Holding levels of the control variables included in Model 4 constant, however, the partial correlation between the two types of deprivation is substantially reduced ($r = .54$, $p < .01$), suggesting that collinearity has smaller effects on estimates in the full model. Furthermore, the largest variance inflation factor (VIF) in the full model is 4.36, which is not large enough to be worrisome (though the standard is admittedly arbitrary, most researchers use values of about seven to indicate problematic multicollinearity).

Third, in the full models, both types of deprivation have significant and positive relationships with crime for all four outcomes. However, the standardized effect size is always larger for absolute deprivation than relative deprivation. Of the variables evidencing significant relationships with the crime outcomes, relative deprivation tends to have one of the weakest relationships, while absolute deprivation has a comparatively moderate relationship. Finally, there are several control variables that consistently display statistically significant relationships to crime in theoretically predicted directions, often having larger associations than either type of deprivation. These include population size (transformed with the natural log), vacant housing, and racial heterogeneity for all four outcomes, and urbanization, residential stability, and foreign-born for three of the four crime types. The proportion of young adults also has a significant relationship with all four crime outcomes, but in an unexpected negative direction. It is possible the age range employed here is slightly higher (older) than the true crime-prone years, and that individuals in the 18-24 years old range are less crime-prone than expected, thus resulting in the negative relationship. Although there were some consistent patterns, there were also some differences that I will explain in greater detail below.

Table 3 displays the results of the regressions using total crimes reported as the outcome. The results are consistent with the general patterns outlined above, with several exceptions. When both types of deprivation are included in Model 3, absolute deprivation no longer has a significant relationship with total crime, while relative deprivation remains significantly and positively related. While both types of deprivation, singly or together, predict a significant amount of variation in total crime in earlier models, the inclusion of the other structural covariates alongside measures of absolute and relative deprivation in Model 4 substantially increases the amount of variance in total crime explained. In the final model, about 60% (R^2 = .60) of the variation in total crime rates across counties is explained by variation in the full set of predictors.

Table 3. OLS Regressions of 1990 Total UCR Offenses (logged) (N = 678)

	Model 1				Model 2				Model 3				Model 4			
	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta
Absolute deprivation	0.20	**	(0.02)	0.32	-		-	-	0.05		(0.03)	0.09	0.08	**	(0.03)	0.13
Relative deprivation	-		-	-	6.98	**	(0.68)	0.37	5.75	**	(1.03)	0.30	1.70	*	(0.78)	0.09
Total population (ln)	-		-	-	-		-	-	-		-	-	0.11	**	(0.02)	0.20
Urbanization	-		-	-	-		-	-	-		-	-	0.83	**	(0.10)	0.35
Young adults	-		-	-	-		-	-	-		-	-	-1.47	*	(0.57)	-0.08
Vacant housing	-		-	-	-		-	-	-		-	-	1.22	**	(0.37)	0.09
Owner-occupied housing	-		-	-	-		-	-	-		-	-	-0.62		(0.33)	-0.10
Residential stability	-		-	-	-		-	-	-		-	-	-1.46	**	(0.28)	-0.19
Hispanic	-		-	-	-		-	-	-		-	-	0.01		(0.23)	0.00
Foreign-born	-		-	-	-		-	-	-		-	-	-1.19	*	(0.51)	-0.10
Racial heterogeneity	-		-	-	-		-	-	-		-	-	0.47	**	(0.10)	0.16
Constant	8.32	**	(0.02)		5.51	**	(0.27)		6.01	**	(0.42)		6.88	**	(0.47)	
R^2	0.10				0.14				0.14				0.60			

*p<.05 **p<.01

To examine the possibility that the associations of absolute and relative deprivation with crime are dissimilar across substantively different types of crime, the total crime rate was separated into violent and property crime rates. It is possible that the mechanisms linking the types of deprivation to crime vary for different classes of crime. For example, feelings of frustration/aggression engendered by conflict or strain could explain violent crime as an "outlet" for feelings of hostility or anger caused by absolute deprivation; property offenses would act as a coping mechanism that reduces strain by helping to meet socially expected norms of economic success (through socially deviant means) without implying negative emotions such as anger.

Table 4 presents the results of the regression models predicting violent crime rates. The findings are congruent with the general patterns discussed above. Unlike the total crime analysis, both absolute deprivation and relative deprivation remain positively and significantly related to violent crime when included together in Model 3. However, the size of the coefficient for relative deprivation is substantially reduced and the standard error is more than tripled, indicating that collinearity substantially reduces the unique variance attributed to relative deprivation. One notable departure in the violent crime models is that the proportion of foreign-born within the county has only a marginally significant ($p < .10$) relationship with violent crime, but this is the only outcome where this is the case. Mirroring the total crime analysis, the variance in violent crime rates explained by the full model ($R^2 = .62$) is roughly triple the amount explained by either type of deprivation alone or together without controls.

Table 4. OLS Regressions of 1990 Violent UCR Offenses (logged) (N = 678)

	Model 1				Model 2				Model 3				Model 4			
	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta
Absolute deprivation	0.40	**	(0.03)	0.44	-		-	-	0.23	**	(0.05)	0.25	0.16	**	(0.04)	0.18
Relative deprivation	-		-	-	11.90	**	(0.93)	0.44	6.73	**	(1.40)	0.25	2.58	*	(1.08)	0.10
Total population (ln)	-		-	-	-		-	-	-		-	-	0.20	**	(0.03)	0.25
Urbanization	-		-	-	-		-	-	-		-	-	0.54	**	(0.13)	0.16
Young adults	-		-	-	-		-	-	-		-	-	-3.36	**	(0.80)	-0.13
Vacant housing	-		-	-	-		-	-	-		-	-	1.47	**	(0.51)	0.08
Owner-occupied housing	-		-	-	-		-	-	-		-	-	-0.79		(0.45)	-0.09
Residential stability	-		-	-	-		-	-	-		-	-	-1.18	**	(0.39)	-0.11
Hispanic	-		-	-	-		-	-	-		-	-	-0.52		(0.32)	-0.06
Foreign-born	-		-	-	-		-	-	-		-	-	-1.39		(0.71)	-0.08
Racial heterogeneity	-		-	-	-		-	-	-		-	-	1.54	**	(0.15)	0.37
Constant	5.85	**	(0.03)		1.06	**	(0.38)		3.14	**	(0.56)		3.00	**	(0.65)	
R^2	0.20				0.19				0.22				0.62			

*p<.05 **p<.01

The relationship between deprivation and property crime was also examined; the results of this analysis are presented in Table 5. Like the violent crime models, the results are very similar to those of the total crime models. In fact, in terms of the size, direction, and statistical significance of the predicted relationships, the property crime models are almost identical to the total crime models. This is not surprising, given that property crime is far more common than violent crime and thus contributes more to the total crime rates than violent crime (U.S. Department of Justice 1989; 1990; 1991; 1999; 2000; 2001). As in the total crime models, when both types of deprivation are included together (Model 3), only relative deprivation remains statistically significantly related to property crime. Absolute deprivation is again significant in the full model (Model 4), along with relative deprivation. Introducing the structural controls into the model greatly increases the amount of variance in property crime levels that is explained; the full model explains between almost five to seven times more of the variance in property crime (R^2 = .58) than absolute deprivation, relative deprivation, or both.

Table 5. OLS Regressions of 1990 Property UCR Offenses (logged) (N = 678)

	Model 1			Model 2			Model 3			Model 4		
	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta
Absolute deprivation	0.18 **	(0.02)	0.29	-	-	-	0.03	(0.03)	0.05	0.07 *	(0.03)	0.11
Relative deprivation	-	-		6.50 **	(0.67)	0.35	5.75 **	(1.02)	0.31	1.74 *	(0.78)	0.09
Total population (ln)	-	-		-	-	-	-	-	-	0.11 **	(0.02)	0.19
Urbanization	-	-		-	-	-	-	-	-	0.86 **	(0.10)	0.37
Young adults	-	-		-	-	-	-	-	-	-1.25 *	(0.58)	-0.07
Vacant housing	-	-		-	-	-	-	-	-	1.21 **	(0.37)	0.09
Owner-occupied housing	-	-		-	-	-	-	-	-	-0.54	(0.33)	-0.09
Residential stability	-	-		-	-	-	-	-	-	-1.53 **	(0.28)	-0.21
Hispanic	-	-		-	-	-	-	-	-	0.09	(0.23)	0.02
Foreign-born	-	-		-	-	-	-	-	-	-1.25 *	(0.51)	-0.11
Racial heterogeneity	-	-		-	-	-	-	-	-	0.38 **	(0.11)	0.13
Constant	8.22 **	(0.02)		5.61 **	(0.27)		5.91 **	(0.41)		6.82 **	(0.47)	
R^2	0.08			0.12			0.12			0.58		

*p<.05 **p<.01

The final set of 1990 analyses look at homicide rates. The UCR measure of homicide is widely believed to be relatively valid and suffer from less underreporting bias than other crimes (Kovandzic, Vieraitis, and Yeisley 1998). This dependent variable was used so that the results of this analysis would be comparable to the large body of work in the deprivation/crime literature that uses homicide as the outcome (Bailey 1984; Kovandzic, Vieraitis, and Yeisley 1998; Krivo and Peterson 2000; Land, McCall, and Cohen 1990; Messner 1982; Messner and Golden 1992; Messner and Tardiff 1986b; Shihadeh and Ousey 1998; Wang and Arnold 2008; Williams 1984). Table 6 presents the results of the homicide-only models, which are congruent with those found in the total, violent, and property crime analyses. A slightly different set of control variables have significant relationships with the outcome than in previous analyses. Homicide is the only outcome that is not significantly related to urbanization. The statistically significant relationship between residential stability and the previous three crime outcomes is also absent. Also departing from previous findings, owner-occupied housing (b = -.97, p < .01) and the proportion of Hispanics (b = -.57, p < .01) are significantly related to homicide in the expected negative direction, though the relationships are relatively weak (Beta = -.12 and -.08, respectively).

Table 6. OLS Regressions of 1990 Homicide UCR Offenses (logged) (N = 678)

	Model 1				Model 2				Model 3				Model 4			
	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta
Absolute deprivation	0.44	**	(0.02)	0.58	-		-	-	0.37	**	(0.04)	0.49	0.20	**	(0.03)	0.27
Relative deprivation	-		-		11.22	**	(0.77)	0.49	2.71	*	(1.10)	0.12	1.91	*	(0.89)	0.08
Total population (ln)	-		-		-		-	-	-		-	-	0.09	**	(0.02)	0.13
Urbanization	-		-		-		-	-	-		-	-	-0.16		(0.11)	-0.06
Young adults	-		-		-		-	-	-		-	-	-4.73	**	(0.65)	-0.22
Vacant housing	-		-		-		-	-	-		-	-	1.07	*	(0.42)	0.07
Owner-occupied housing	-		-		-		-	-	-		-	-	-0.97	**	(0.37)	-0.12
Residential stability	-		-		-		-	-	-		-	-	-0.63		(0.32)	-0.07
Hispanic	-		-		-		-	-	-		-	-	-0.57	*	(0.27)	-0.08
Foreign-born	-		-		-		-	-	-		-	-	-1.63	**	(0.58)	-0.11
Racial heterogeneity	-		-		-		-	-	-		-	-	2.00	**	(0.12)	0.56
Constant	1.73	**	(0.02)		-2.79	**	(0.31)		0.64		(0.44)		0.78		(0.54)	
R^2	0.33				0.24				0.34				0.65			

*p<.05 **p<.01

The relative size of the coefficients for the variables are similar to previous analyses, but unlike the other three outcomes, only one structural covariate (racial heterogeneity) has a relationship with homicide that is larger than that of absolute deprivation; the standardized coefficient of absolute deprivation for homicide (Beta = .27) is much larger than for property, violent, or total crime. Also unlike previous analyses, a much larger proportion of the variance in homicide rates (between a quarter and a third) is explained by the variance in absolute or relative deprivation or both, while the amount of variance in homicide rates explained by the full model (R^2 = .65) is roughly the same size as the full models for the previous three outcomes.

In combination, not only do all four of the 1990 cross-sectional analyses suggest that absolute deprivation has a stronger relationship with crime than relative deprivation, but also that several other structural conditions of communities have a significant association with all four classifications of crime, often larger than either type of deprivation. In order to see if similar patterns hold at a second distinct point in time, I now turn to cross-sectional regression analyses of the same relationships for the year 2000.

Crime and Deprivation in 2000

Tables 7 through 10 present the results of the same analytic strategy applied to the total, violent, property and homicide offense rates (using the natural log) for 2000. The results for all four sets of models are very similar to those using the 1990 data and the patterns of relationships that emerge are generally congruent with the 1990 analyses, with several notable differences. As in 1990, absolute and relative deprivation are always significantly related to crime when used as the sole predictor of the outcome (Models 1 and 2), and in the theoretically expected positive direction. In a minor departure from the 1990 models, both types of deprivation remain significantly and positively related to all four outcomes when included together in Model 3 without controls. Moreover, the standardized coefficient of absolute deprivation in the third model is always larger than the standardized coefficient of relative deprivation, ranging between roughly two and four times larger. The correlation between the two deprivation measures is large and significant ($r = .82$, $p < .01$), as in 1990, suggesting that collinearity may influence the estimates. However, like before, holding levels of the control variables included in the full model constant substantially reduces the partial correlation between absolute and relative deprivation ($r = .56$, $p < .01$), implying that collinearity between them is less problematic in Model 4. The largest variance inflation factor (VIF) in the 2000 full model is 5.09, which is not large enough to indicate troublesome levels of multicollinearity in the model.

In the full models, absolute deprivation always has a stronger relationship than relative deprivation with crime, net of the controls, paralleling the 1990 analyses. One notable difference between the 1990 and 2000 analyses, however, is that absolute deprivation consistently has the largest standardized coefficient for all four outcomes in the full model, whereas in 1990 its relative size was moderate. Additionally, while the relationship between relative deprivation and all four outcomes are comparatively weak in the full models (as in 1990), in 2000 the relationship is only statistically significant for two crime outcomes (not all four). Finally, a number of control variables have consistent, statistically significant relationships with all four crime outcomes in the expected directions, including population size (the natural log transformation), residential stability, and foreign-born. The proportion of young adults is also significantly related to all four outcomes, but once again in an unexpected negative direction. Urbanization and racial heterogeneity are significantly related to three of the four outcomes in the expected positive direction. In a noteworthy departure from the 1990 cross-sectional findings, vacant housing is not significantly related to any of the crime outcomes, whereas it was previously significantly related to all four. There are a number of differences between the general patterns to emerge in 2000 and specific outcomes, which I will explain in greater detail below. It should also be noted that the amount of variance in the outcome explained by Models 1 through 3 is consistently larger in 2000 than in 1990, though it is roughly similar for the full models.

Table 7 displays the results of the total crime regressions. The results are consistent with the patterns described above, with one exception. While the relationship between relative deprivation and total crime was significant in models 1-3, once the control variables are included in the full model (Model 4), this relationship disappears. This suggests that while there may be a significant correlation between relative deprivation and total crime, the partial correlation is non-significant once the control variables are held constant. In addition, while the deprivation measures, both alone and together, predict a significant amount of variance in the outcome, including the other structural covariates in Model 4 more than doubles the amount of variance explained (R^2 = .52).

Table 7. OLS Regressions of 2000 Total UCR Offenses (logged) (N = 678)

	Model 1			Model 2			Model 3			Model 4		
	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta
Absolute deprivation	0.29 **	(0.02)	0.48	-	-	-	0.21 **	(0.03)	0.36	0.26 **	(0.04)	0.44
Relative deprivation	-	-	-	8.23 **	(0.64)	0.44	2.76 *	(1.08)	0.15	1.22	(0.99)	0.07
Total population (ln)	-	-	-	-	-	-	-	-	-	0.09 **	(0.02)	0.17
Urbanization	-	-	-	-	-	-	-	-	-	0.53 **	(0.11)	0.21
Young adults	-	-	-	-	-	-	-	-	-	-3.04 **	(0.64)	-0.19
Vacant housing	-	-	-	-	-	-	-	-	-	0.22	(0.45)	0.02
Owner-occupied housing	-	-	-	-	-	-	-	-	-	-0.01	(0.33)	0.00
Residential stability	-	-	-	-	-	-	-	-	-	-3.14 **	(0.33)	-0.39
Hispanic	-	-	-	-	-	-	-	-	-	-0.07	(0.22)	-0.01
Foreign-born	-	-	-	-	-	-	-	-	-	-2.03 **	(0.44)	-0.24
Racial heterogeneity	-	-	-	-	-	-	-	-	-	0.30 *	(0.11)	0.11
Constant	8.08 **	(0.02)		4.78 **	(0.26)		6.97 **	(0.43)		8.09 **	(0.54)	
R^2	0.23			0.20			0.24			0.52		

*p<.05 **p<.01

The total crime rate was again split into two separate categories, violent and property crime, to examine the possibility that the relationships between the primary independent variables and crime are moderated by the nature of the crime in question. Regression results predicting violent crime rates are presented in Table 8 and are consistent with the general patterns found for the 2000 analyses. There are two small differences between these results and those from the analyses of violent crime in 1990. As previously mentioned, vacant housing does not exhibit a significant relationship with violent crime in 2000, though both in 1990 and

2000 the standard coefficient size is relatively small. Secondly, the proportion foreign-born does have a significant relationship in 2000 that did not appear in the 1990 analyses. As with the 1990 data, the amount of variance in violent crime explained by the deprivation-only models is larger than in the total crime models, which supports the conclusion that deprivation of either type is a better predictor of violent crime than of total crime. Moreover, like the 2000 total crime models, both measures of deprivation predict a significant amount of variance in the outcome in Models 1 through 3 (between 29 and 35 percent), but there is a substantial increase in the variance explained by the full model (R^2 = .59).

Table 8. OLS Regressions of 2000 Violent UCR Offenses (logged) (N = 678)

	Model 1				Model 2				Model 3				Model 4			
	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta
Absolute deprivation	0.47	**	(0.03)	0.58	-		-	-	0.33	**	(0.04)	0.41	0.31	**	(0.05)	0.38
Relative deprivation	-		-	-	13.63	**	(0.81)	0.54	5.26	**	(1.35)	0.21	4.10	**	(1.23)	0.16
Total population (ln)	-		-	-	-		-	-	-		-	-	0.13	**	(0.03)	0.19
Urbanization	-		-	-	-		-	-	-		-	-	0.35	*	(0.14)	0.10
Young adults	-		-	-	-		-	-	-		-	-	-5.05	**	(0.81)	-0.23
Vacant housing	-		-	-	-		-	-	-		-	-	0.88		(0.56)	0.05
Owner-occupied housing	-		-	-	-		-	-	-		-	-	-0.06		(0.41)	-0.01
Residential stability	-		-	-	-		-	-	-		-	-	-2.68	**	(0.41)	-0.25
Hispanic	-		-	-	-		-	-	-		-	-	-0.35		(0.28)	-0.05
Foreign-born	-		-	-	-		-	-	-		-	-	-1.78	**	(0.55)	-0.16
Racial heterogeneity	-		-	-	-		-	-	-		-	-	1.05	**	(0.14)	0.29
Constant	5.69	**	(0.03)		0.21		(0.33)		3.57	**	(0.54)		3.75	**	(0.68)	
R^2	0.33				0.29				0.35				0.59			

*p<.05 **p<.01

The results of the models of deprivation and property crime in 2000, displayed in Table 9, are congruent with previous analyses. As in 1990, the results are almost identical to the total crime models, with one exception. Racial heterogeneity, which has a significant relationship with total crime, does not have a statistically significant association with property crime. This is the only outcome where racial heterogeneity does not evidence a significant relationship in the full model, suggesting that its marginally significant association with total crime is primarily driven by a strong relationship with violent crime, rather than property crime. An examination of the standardized coefficients of racial heterogeneity supports this conclusion; the relationship is much stronger with violent crime (Beta = .29) than with property crime (Beta = .09). Though the relationships were significant for all four outcomes in 1990, the same pattern of coefficient size is found in those analyses. There are two departures from the 1990 property crime models that are part of the general pattern of results in 2000. Relative deprivation has a non-significant relationship with property crime in the full model (mirroring the total crime model), and vacant housing fails to demonstrate a significant relationship with the outcome. The amount of variance in property crime explained by either absolute deprivation, relative deprivation, or both is substantial, roughly 20%; however, the full model explains more than double that amount (R^2 = .49).

Table 9. OLS Regressions of 2000 Property UCR Offenses (logged) (N = 678)

	Model 1			Model 2			Model 3			Model 4		
	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta
Absolute deprivation	0.27 **	(0.02)	0.45	-	-	-	0.20 **	(0.03)	0.34	0.26 **	(0.04)	0.44
Relative deprivation	-	-	-	7.65 **	(0.64)	0.42	2.54 *	(1.08)	0.14	1.02	(1.00)	0.06
Total population (ln)	-	-	-	-	-	-	-	-	-	0.09 **	(0.02)	0.17
Urbanization	-	-	-	-	-	-	-	-	-	0.56 **	(0.11)	0.22
Young adults	-	-	-	-	-	-	-	-	-	-2.83 **	(0.66)	-0.18
Vacant housing	-	-	-	-	-	-	-	-	-	0.16	(0.45)	0.01
Owner-occupied housing	-	-	-	-	-	-	-	-	-	0.05	(0.34)	0.01
Residential stability	-	-	-	-	-	-	-	-	-	-3.22 **	(0.33)	-0.40
Hispanic	-	-	-	-	-	-	-	-	-	-0.02	(0.23)	0.00
Foreign-born	-	-	-	-	-	-	-	-	-	-2.12 **	(0.45)	-0.25
Racial heterogeneity	-	-	-	-	-	-	-	-	-	0.23	(0.12)	0.09
Constant	7.98 **	(0.02)		4.90 **	(0.26)		6.95 **	(0.44)		8.12 **	(0.55)	
R^2	0.21			0.17			0.21			0.49		

*p<.05 **p<.01

Table 10 presents the results of the last set of 2000 analyses, which model the relationships between deprivation and homicide rates. These models are similar to both the earlier 1990 homicide analysis and the other three outcomes in 2000. The general pattern of results for the first three models is identical to the other outcomes, but the full model displays slightly different relationships than for violent, property, and total crime, as was the case in 1990. Homicide is the only outcome where urbanization does not have a statistically significant association and is also the only time the proportion of Hispanics is significant related to crime in the theoretically expected direction, though its relationship is again small (Beta = -.10). Unlike the full model of homicide in 1990, however, neither owner-occupied housing nor vacant housing has a significant relationship with homicide in 2000, though this parallels the findings of the 2000 analyses in general. Absolute and relative deprivation, singly and together, again explain more of the variance in homicide (between 30% and 40%) than the other three outcomes, though the differences are not as substantial as in 1990. The variance explained increases to about 60% (R^2 = .61) after the control variables are added in the full model.

Table 10. OLS Regressions of 2000 Homicide UCR Offenses (logged) (N = 678)

	Model 1			Model 2			Model 3			Model 4		
	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta
Absolute deprivation	0.44 **	(0.02)	0.62	-	-	-	0.37 **	(0.04)	0.52	0.31 **	(0.04)	0.43
Relative deprivation	-	-	-	12.19 **	(0.71)	0.55	2.85 *	(1.14)	0.13	2.82 **	(1.06)	0.13
Total population (ln)	-	-	-	-	-	-	-	-	-	0.13 **	(0.02)	0.21
Urbanization	-	-	-	-	-	-	-	-	-	-0.15	(0.12)	-0.05
Young adults	-	-	-	-	-	-	-	-	-	-4.15 **	(0.69)	-0.22
Vacant housing	-	-	-	-	-	-	-	-	-	-0.43	(0.48)	-0.03
Owner-occupied housing	-	-	-	-	-	-	-	-	-	-0.26	(0.35)	-0.04
Residential stability	-	-	-	-	-	-	-	-	-	-1.04 **	(0.35)	-0.11
Hispanic	-	-	-	-	-	-	-	-	-	-0.60 *	(0.24)	-0.10
Foreign-born	-	-	-	-	-	-	-	-	-	-1.98 **	(0.47)	-0.20
Racial heterogeneity	-	-	-	-	-	-	-	-	-	1.36 **	(0.12)	0.42
Constant	1.42 **	(0.02)		-3.47 **	(0.29)		0.27	(0.46)		-0.49	(0.58)	
R^2	0.39			0.30			0.39			0.61		

*p<.05 **p<.01

In sum, the 2000 analyses are both congruent with and depart from those using 1990 data. As in all the 1990 models, absolute deprivation is always statistically significantly related to the crime outcome of interest in the full model, and in cases where relative deprivation also displays a significant relationship with crime, its standardized coefficient size is always smaller than that of absolute deprivation. Unlike the 1990 analyses, however, absolute deprivation consistently has the largest standardized coefficient for all four crime outcomes in 2000. In 1990, a number of control variables demonstrated stronger relationships with crime rates than absolute deprivation; this was never the case in 2000.

Crime and Deprivation between 1990-2000

Following the analyses on crime and deprivation in 1990 and 2000, I examined the relationships between absolute and relative deprivation and crime over time, expanding upon previous research that relies almost exclusively on cross-sectional models of deprivation and crime. As previously discussed, the change-score models regress the changes in crime rates between 1990 and 2000 on changes in structural conditions within metropolitan counties (and several independent metropolitan cities) over the same time period. Results from these analyses are expected to be similar to those that emerged with the cross-sectional data, given that the theoretical mechanisms assumed to link either type of deprivation and crime (regardless of which theory is preferred) should operate the same over time as at a single time point. It should be noted that there is little variation in levels of absolute and relative deprivation over time, which likely makes it more difficult to find statistically significant dynamic relationships between deprivation and crime, since change-score models rely heavily on cases which vary on both x and y (Firebaugh 2008).

Tables 11 through 14 present the results of change-score regressions of total crimes, violent and property crimes, and homicides. The strategy used to model the relationships between deprivation, other structural conditions, and crime over time is identical to that used for the 1990 and 2000 cross-sections. The relationships of absolute deprivation changes (Model 1) and relative deprivation changes (Model 2) with changes in crime are examined separately before being included together (Model 3). Potentially spurious relationships are then addressed by adding the set of theoretically relevant controls to the full model (Model 4). Contrary to expectations, the general patterns that emerge from the change-score analyses are somewhat different from the cross-sectional analyses, particularly for the relationships between changes in absolute and relative deprivation with changes in crime. First, only the total and property crime change outcomes are ever significantly related to changes in absolute or relative deprivation, including when each is used as the sole predictor (Models 1 and 2). Second, once the two measures are included together in Model 3, relative deprivation change is no longer a significant predictor, while absolute deprivation change continues to be significantly related to changes in total and property crime. This pattern reverses when the control variables are included in Model 4, where changes in relative deprivation have a statistically significant relationship with changes in total and property crime while changes in absolute deprivation do not. It is possible that the correlation between the two measures of deprivation is affecting the estimates and generating these inconsistencies between Model 3 and Model 4. However, as noted previously, using a change-score model significantly diminishes the correlation between absolute and relative deprivation ($r = .45$, $p < .01$), suggesting that this is less likely in the change-score models than in the cross-sections. In the full model, the partial correlation is even further reduced when holding levels of the control variables constant ($r = .31$, $p < .01$), and the largest VIF in the full models is only 3.29, leading me to believe that multicollinearity is not substantially distorting these results.

Third, even when the associations between changes in absolute and/or relative deprivation and crime change are significant, they are in an unexpected negative direction (though there are no controls included in the models where absolute deprivation has a significant relationship to crime). This implies that increases in deprivation lead to decreases in crime, which seems to conflict with the predictions of several criminological theories. The negative relationship between change in absolute deprivation and total and property crime change (understanding that total crime is largely driven by property crime) may be explained by a rational choice or routine activities framework. Areas with higher levels of absolute deprivation probably contain fewer attractive targets for property crime (such as burglary or auto theft), thus lowering crime rates. Conversely, areas with higher levels of resources have more attractive targets. The negative relationships between relative deprivation change and changes in total and property crime remain after controls are added to the model, making it more likely that the estimates represent reality. It is possible that increasing relative deprivation is being driven by the entry of more individuals at the upper end of the income distribution into a community whose residents generally have lower levels of income (i.e. the beginning stages of gentrification). A negative relationship between relative deprivation and crime could be the result of these individuals using their resources to protect themselves, and by extension their community (including residents at the lower end of the income distribution) from crime. This possibility will be discussed further below.

Fourth, like in the cross-sectional analyses, there are a number of control variables that consistently have significant relationships with crime. The change in the proportion foreign-born is significantly related to changes in all four outcomes. In fact, it always has the largest standardized coefficient of any variable, in the expected negative direction. Changes in urbanization, vacant housing, and heterogeneity are significantly related to change in three of the outcomes in the expected positive direction. Total population change also significantly predicts change in three of the outcomes, but the relationship is unexpectedly negative (though small). Routine activities theory might explain this relationship as an increase in the number of capable guardians (Cohen and Felson 1979). Finally, even when the relationship between changes in relative deprivation and crime change is significant, the association is at best moderate and usually smaller than that of the significant control variables. Some departures from these general patterns did occur, which I will explain below.

Table 11 displays the results of the change-score regressions modeling total crime. The relationships between changes in absolute and relative deprivation, the structural controls, and the outcome are consistent with the general findings discussed above, with two exceptions. First, change in owner-occupied housing has a significant, negative relationship with changes in total crime, consistent with theoretical predictions. Second, the change in the proportion of Hispanics also has a significant relationship in the expected negative direction. While the variance in total crime change explained by changes in absolute and relative deprivation, alone or together, remains statistically significant, the values are much smaller than in the cross-sectional analyses, between 1% and 3%. The change-score full model also fails to account for nearly as much of the variance in the outcome as the cross-sectional analyses; less than 30% of the variance in total crime change is accounted for by variance in the complete set of predictors (R^2 = .28).

Table 11. OLS Change-Score Regressions of Total UCR Offenses, 1990-2000 (N = 678)

	Model 1				Model 2				Model 3				Model 4			
	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta
Absolute deprivation	-663.31	**	(141.21)	-0.18	-		-	-	-613.31	**	(158.26)	-0.16	-155.01		(149.64)	-0.04
Relative deprivation	-		-	-	-13112.43	**	(4830.38)	-0.10	-3753.85		(5356.32)	-0.03	-12457.16	*	(5081.39)	-0.10
Total population (1000's)	-		-	-	-		-	-	-		-	-	-1.88	*	(0.79)	-0.10
Urbanization	-		-	-	-		-	-	-		-	-	2314.35	**	(548.61)	0.15
Young adults	-		-	-	-		-	-	-		-	-	-4945.24		(4697.42)	-0.04
Vacant housing	-		-	-	-		-	-	-		-	-	8844.80	**	(2611.78)	0.13
Owner-occupied housing	-		-	-	-		-	-	-		-	-	-6507.91	*	(2917.29)	-0.08
Residential stability	-		-	-	-		-	-	-		-	-	211.74		(1728.48)	0.00
Hispanic	-		-	-	-		-	-	-		-	-	-8374.10	**	(3071.37)	-0.15
Foreign-born	-		-	-	-		-	-	-		-	-	-15531.46	**	(3950.12)	-0.24
Racial heterogeneity	-		-	-	-		-	-	-		-	-	2481.88	*	(1160.40)	0.08
Constant	-1114.96	**	(56.61)		-1127.77	**	(57.41)		-1118.63	**	(56.88)		-752.94	**	(121.16)	
R^2	0.03				0.01				0.03				0.28			

*p<.05 **p<.01

The change in total crime rates was also divided into the change in violent crime rates and the change in property crime rates. The results of the violent crime change-score analysis are displayed in Table 12. Neither absolute nor relative deprivation change is significantly related to change in violent crime rates in any of the models. In fact, neither type of deprivation change explains more than 1% of the variance in violent crime change, either separately or together. Models 1 through 3 all fail to account for a significant amount of variance in violent crime change. The results of the full model are mostly consistent with the general findings discussed above, though change in violent crime is the only outcome which fails to have a statistically significant relationship with changes in vacant housing. The full model, unlike the partial models, does explain a significant amount of variance in violent crime change (R^2 = .13), indicating that the set of structural controls are much better predictors of changes in violent crime than changes in either type of deprivation.

Table 12. OLS Change-Score Regressions of Violent UCR Offenses, 1990-2000 (N = 678)

	Model 1				Model 2				Model 3				Model 4			
	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta
Absolute deprivation	-38.97		(24.05)	-0.06	-		-	-	-26.06		(26.94)	-0.04	7.96		(27.48)	0.01
Relative deprivation	-		-	-	-1366.85		(813.95)	-0.06	-969.18		(911.93)	-0.05	-1741.03		(933.21)	-0.08
Total population (1000's)	-		-	-	-		-	-	-		-	-	-0.32	*	(0.14)	-0.10
Urbanization	-		-	-	-		-	-	-		-	-	382.22	**	(100.75)	0.14
Young adults	-		-	-	-		-	-	-		-	-	-264.92		(862.69)	-0.01
Vacant housing	-		-	-	-		-	-	-		-	-	148.76		(479.66)	0.01
Owner-occupied housing	-		-	-	-		-	-	-		-	-	-45.65		(535.77)	0.00
Residential stability	-		-	-	-		-	-	-		-	-	582.25		(317.44)	0.08
Hispanic	-		-	-	-		-	-	-		-	-	336.63		(564.06)	0.04
Foreign-born	-		-	-	-		-	-	-		-	-	-3457.12	**	(725.45)	-0.31
Racial heterogeneity	-		-	-	-		-	-	-		-	-	661.44	**	(213.11)	0.13
Constant	-105.64	**	(9.64)		-106.97	**	(9.67)		-106.58	**	(9.68)		-115.63	**	(22.25)	
R^2	0.00				0.00				0.01				0.13			

*p<.05 **p<.01

As in the cross-sectional analyses, the results of the change-score analysis of property crime rates shown in Table 13 are very similar to the change-score analyses of total crime rates. The only difference between the total crime and property crime outcomes is in the full model. Changes in racial heterogeneity and property crime change are not significantly related, though the standard coefficient size (Beta = .07) is similar to the total crime model where the relationship is only marginally significant. This outcome is the only one which fails to evidence a significant relationship with racial heterogeneity in the change-score analyses. Property crime change is also the only outcome besides total crime change to display a statistically significant relationship with changes in owner-occupied housing and the proportion of Hispanics, with almost identical coefficient sizes to those seen in the total crime analysis. The variance in property crime change explained by changes in either absolute deprivation, relative deprivation, or both is again small, though always statistically significant, ranging from 1% to 4%. The full model explains far more of the variance than deprivation change alone (R^2 = .29), but this continues to be much less than is explained by the cross-sectional analyses.

Table 13. OLS Change-Score Regressions of Property UCR Offenses, 1990-2000 (N = 678)

	Model 1			Model 2			Model 3			Model 4		
	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta
Absolute deprivation	-645.74 **	(125.10)	-0.19	-	-	-	-613.75 **	(140.22)	-0.19	-196.08	(132.06)	-0.06
Relative deprivation	-	-	-	-11767.09 **	(4292.79)	-0.10	-2401.85	(4745.98)	-0.02	-10510.07 *	(4484.18)	-0.09
Total population (1000's)	-	-	-	-	-	-	-	-	-	-1.55 *	(0.70)	-0.09
Urbanization	-	-	-	-	-	-	-	-	-	1933.97 **	(484.13)	0.14
Young adults	-	-	-	-	-	-	-	-	-	-4570.22	(4145.34)	-0.04
Vacant housing	-	-	-	-	-	-	-	-	-	8882.02 **	(2304.82)	0.15
Owner-occupied housing	-	-	-	-	-	-	-	-	-	-6665.89 *	(2574.43)	-0.09
Residential stability	-	-	-	-	-	-	-	-	-	-266.15	(1525.33)	-0.01
Hispanic	-	-	-	-	-	-	-	-	-	-8617.35 **	(2710.40)	-0.17
Foreign-born	-	-	-	-	-	-	-	-	-	-12035.85 **	(3485.86)	-0.20
Racial heterogeneity	-	-	-	-	-	-	-	-	-	1883.05	(1024.02)	0.07
Constant	-1009.93 **	(50.15)		-1021.43 **	(51.02)		-1012.28 **	(50.40)		-641.14 **	(106.92)	
R^2	0.04			0.01			0.04			0.29		

*p<.05 **p<.01

Table 14 displays the results of the final set of change-score analyses, which model the relationships between changes in absolute and relative deprivation and homicide rates over the 1990-2000 period. As in the violent crime analysis, neither changes in absolute deprivation nor relative deprivation have a significant relationship to the outcome in any of the models. The variance in homicide change explained by changes in the deprivation measures singly or together is always less than 1% and is never statistically significant. The significant relationships that emerge in the full model are noticeably different from the general patterns described above, which is congruent with the results of the cross-sectional analyses. This is the only outcome in the change-score analyses which does not have a significant relationship with changes in total population. Change in homicide is also the only outcome that is not significantly affected by urbanization changes, mirroring the results of the 1990 and 2000 analyses. Finally, change in residential stability is significantly related to homicide change, unlike the other three outcomes. The full model explains a significant amount of variance in homicide change (R^2 = .11), suggesting that changes in structural conditions besides deprivation are more important in predicting changes in homicide, though this is still a substantially smaller amount of variance explained than in either of the cross-sectional homicide analyses.

Table 14. OLS Change-Score Regressions of Homicide UCR Offenses, 1990-2000 (N = 678)

	Model 1			Model 2			Model 3			Model 4		
	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta	b	(SE)	Beta
Absolute deprivation	-0.40	(0.37)	-0.04	-	-	-	-0.66	(0.41)	-0.07	-0.45	(0.42)	-0.05
Relative deprivation	-	-	-	9.35	(12.39)	0.03	19.36	(13.87)	0.06	-5.55	(14.40)	-0.02
Total population (1000's)	-	-	-	-	-	-	-	-	-	0.00	(0.00)	-0.03
Urbanization	-	-	-	-	-	-	-	-	-	2.91	(1.55)	0.07
Young adults	-	-	-	-	-	-	-	-	-	-16.69	(13.31)	-0.05
Vacant housing	-	-	-	-	-	-	-	-	-	18.41 *	(7.40)	0.11
Owner-occupied housing	-	-	-	-	-	-	-	-	-	3.30	(8.27)	0.02
Residential stability	-	-	-	-	-	-	-	-	-	9.85 *	(4.90)	0.09
Hispanic	-	-	-	-	-	-	-	-	-	-10.71	(8.71)	-0.07
Foreign-born	-	-	-	-	-	-	-	-	-	-32.94 **	(11.20)	-0.20
Racial heterogeneity	-	-	-	-	-	-	-	-	-	18.34 **	(3.29)	0.25
Constant	-2.21 **	(0.15)		-2.20 **	(0.15)		-2.19 **	(0.15)		-3.12 **	(0.34)	
R^2	0.00			0.00			0.00			0.11		

*p<.05 **p<.01

In sum, the results of the change-score analyses differ substantially from the cross-sectional analyses across all four of the crime outcomes. The change in absolute deprivation fails to become significantly related to changes in crime rates in all four full models, while changes in relative deprivation are significantly related only to changes in total crime and property crime rates. Moreover, even when the relationships between changes in the deprivation measures and changes in crime are statistically significant, they are unexpectedly negative; this counterintuitive finding diverges from theoretical expectations. Finally, the relationships between the proportion foreign-born with all four outcomes were substantially larger in the change-score analyses than in cross-section. While the proportion foreign-born had a significant relationship with most of the outcomes for both cross-sectional analyses, the associations were comparatively moderate. In the change-score analyses, they always have the strongest relationship in the full models. I will now further discuss the consistent and divergent patterns that emerged from the cross-sectional and change-score analyses and consider some of their implications for criminological theory. I will also point out some of the shortcomings of the current research and suggest directions for future work.

Discussion and Conclusions

A number of the above findings warrant further consideration and discussion. Central to this study were several questions on the relationships between deprivation and crime, including the comparative importance of absolute and relative deprivation and the stability of these relationships over time. The findings indicate that none of these questions can be answered unequivocally. In the cross-sectional analyses at 1990 and 2000, both types of deprivation typically had statistically significant relationships with the outcome, but the measure of absolute deprivation had a universally stronger association with total, violent, property and homicide crime outcomes than the measure of relative deprivation. However, relative deprivation was also significantly related to all four outcomes in the 1990 cross-sectional analyses and two of the four (violent offenses and homicide) in 2000, suggesting that both types of deprivation play an important role in predicting area levels of crime. This pattern is congruent with previous research which finds measures of both absolute and relative deprivation to be significantly related to crime (Danziger 1976; Hsieh and Pugh 1993; Loftin and Hill 1974), while also lending support to researchers who conclude that absolute deprivation is the more important of the two (Kposowa, Breault, and Harrison 1995; Messner 1982; Patterson 1991).

The relationships between deprivation and crime found in the change-score analyses differ substantially from the cross-sectional analyses. Unlike the previous findings, the change-score models indicate that absolute and relative deprivation are significantly related only to property crime (assuming that total crime is driven primarily by property crime). Moreover, even when these associations are statistically significant, they are in unexpected negative directions, implying that increases in absolute or relative deprivation lead to less crime (or conversely, decreases in deprivation lead to more crime). While these results seem counterintuitive at first glance, existing theories of crime can account for these negative relationships. For instance, as previously mentioned, the negative relationship between absolute deprivation and crime could be the result of fewer attractive targets within an area, whether property (e.g. cars or homes containing items worth committing burglary for) or people (e.g. residents worth robbing); there is less crime because the rewards for criminal behavior are fewer (Cohen and Felson 1979) and not worth risking the costs of detection and punishment (Chiu and Madden 1998). The converse could also be true, if areas with higher levels of resources offer more attractive targets for crime.

It is slightly more difficult to explain the negative relationship between relative deprivation and crime in the change-score analyses. This result implies that increases in relative deprivation between 1990 and 2000 led to decreases in property crime (and as a result, total crime) over the same period. Conversely, areas which experienced decreases in relative deprivation (i.e. residents' incomes became more similar) saw increases in crime. This outcome seems to contradict existing macro-level criminological theories, which usually assume that increased homogeneity of resources attenuates the mechanisms linking deprivation to crime (e.g. negative emotions, weakened social bonds, or the coexistence of motivated offenders and attractive targets), resulting in lower levels of crime. However, recent extensions of social disorganization and collective efficacy theory offer one possible explanation for this finding. While earlier research within this framework focused primarily on social ties between area residents and the levels of informal social control that were assumed to result, contemporary work has begun to examine the role of institutions and extra-community relations in creating social capital and control (Morenoff, Sampson, and Raudenbush 2001; Warner and Rountree 1997). Effective control is not only the result of associations and ties within an area, but is also dependent upon the community's ability to access resources from external sources; for example, to engage in positive relationships with police agencies or exercise political influence (Bursik and Grasmick 1993b; Rose and Clear 1998). It is likely that affluent residents are better equipped to "secure public goods and services from sources outside the neighborhood" (Rose and Clear 1998, p. 445) than poorer residents (see also Triplett, Gainey, and Sun 2003). If increases in relative deprivation are being driven by people at the upper end of the income distribution moving into areas that already contain people who fall lower in the distribution (such as the beginning stages of gentrification), then it is likely that the presence of more affluent individuals will lead to increased levels of public control and thus less crime. On the other hand, if affluent individuals move out of an area, statistical inequality will go down along with mean levels of resources. This parallels Wilson's (1987) "concentrated disadvantage" mechanism, and it seems likely that such a scenario would lead to weaker public control and result in higher levels of crime. Such a mechanism also seems plausible given that there is a "floor effect" for poverty, but no parallel "ceiling effect" for affluence. Levels of inequality are bounded at the lower end of the resource distribution, but not at the higher end; there is an infinite range for inequality to expand through increases in high-income residents. This interpretation, however, depends upon the assumption that new, more affluent residents are not displacing older, poorer residents; otherwise, while mean levels of absolute deprivation would decrease, relative deprivation would remain fairly stable.

There is one other notable finding from this research that should be discussed. The proportion of foreign-born residents (and changes in the proportion over time), out of all the control variables, had one of the most consistent significant relationships across all of the crime outcomes. This variable was significantly and negatively related to crime in every analysis, save one where its significance level was exactly at $p = .05$. This result is congruent with the growing body of research addressing the relationships between immigration and crime (see Sampson 2008 for an overview). While the mechanisms linking foreign-born populations to lower crime remain highly debated, the current research provides further evidence that this relationship exists and is relatively strong, particularly considering that the significant associations remain after controlling for a wide range of economic and other structural conditions. This pattern is particularly important in the context of the American crime decline between 1990 and 2000. I am aware of no research that addresses a potential link between changes in the foreign-born population and drops in crime levels over this period, but given these results it is possible that decreases in crime rates are being driven by increases in the population of this low-risk group. Future research should investigate the relationship between immigration and the crime drop further.

There are several shortcomings of this study that may be driving the somewhat inconsistent findings on the relationships between absolute and relative deprivation and crime. As noted previously, using a multi-item measure of absolute deprivation and a single-item measure of relative deprivation may be "stacking the deck" and making it more likely that absolute deprivation will evidence a stronger relationship to crime outcomes than relative deprivation does. However, the supplemental analysis of homicide in 1990 indicates that a single-item measure of absolute deprivation, poverty, has a relationship with the outcome that is very similar to the multi-item factor measure. Additionally, the relationship between relative deprivation and homicide is practically unchanged when highly collinear variables (unemployment, female-headed households, and education) are excluded from the full model in the supplemental analysis. This leads me to conclude that the use of the factor measure does not substantially alter my interpretations and conclusions regarding the relationships between absolute and relative deprivation and crime.

Multicollinearity between the deprivation measures remains a persistent issue. While the factor-weighted measure of absolute deprivation was used to minimize the collinearity with relative deprivation, these measures remained strongly correlated, which could lead to one of the estimation errors discussed earlier in this paper. However, I believe the use of a factor-weighted measure is still a methodological improvement over earlier research. Using such a measure, while not eliminating collinearity between the types of deprivation, does remove a significant amount of multicollinearity between the usual measure of absolute deprivation, poverty, and a number of common control variables such as female-headed households, education, and unemployment. Rotated factor analyses showed that these four variables all load strongly on a single underlying latent construct, so the use of such the factor-weighted measure is appropriate.

Thirdly, the application of a change-score model to enduring questions on deprivation and crime is not without its problems. Change-score and related models (e.g. fixed- and random-effects) tap into the dynamic nature of these relationships in a way that cross-sectional models cannot, but there are drawbacks to their use. First-difference models like change-scores only remove the effects of *time-stable* unmeasured heterogeneity between units, such as geographic location (Allison 1990; Halaby 2004). Omitted variable bias can remain problematic if the sources of unmeasured heterogeneity change over time, both in terms of their presence/concentration and also their effects (i.e. the relationship changes over time). There can also be a significant loss of variance on both the predictor and outcome variables. This is of particular importance for the deprivation variables, given that there is little variance over time for both. First-difference models strongly rely on how much Y changes for those units where X also changes over time (Firebaugh 2008), which can substantially limit how many cases in the sample add to variance in the outcome. This tradeoff is inherent to such methods. While there may be less variance to explain, the remaining variance may be of “higher quality” (p. 137) because the effects of time-stable unmeasured variables are removed.

Another issue is the difficulty in making strong causal arguments about the relationships between deprivation and crime when using a change-score method. Removing the effects of unmeasured time-stable variables makes the effect of unobserved sources of heterogeneity less problematic for causal inference. However, because the change-score model relies on only two time points, regression estimates are still based on unit-level deviation from the sample-level mean change, rather than unit-level mean values. As such, these estimates rely on between-unit, rather than within-unit, variance and the change-score method is not a counterfactual approach to causal inference. To limit analyses to within-unit variance, as in a fixed-effects model, requires a third time point, where each unit acts as its own reference and stronger causal inferences can be drawn, though this remains a non-counterfactual model and threats to causal inference still exist (such as time- or unit-variant unmeasured heterogeneity). Future research should expand the time frame of the current study to a third time point (e.g. 1980 or 2010) in order to apply a fixed-effects model to the absolute/relative deprivation and crime question, or employ a counterfactual approach such as a natural experiment or propensity model to better approximate causality.

Finally, the relationships found here could be dependent on the sample used. Currently, there is much debate over the proper level of aggregation to employ in studies of macro-level covariates of crime, including economic conditions. An argument was made for the use of counties (and unincorporated cities) comprising metropolitan statistical areas. Additionally, it is implicit in general theories of crime that the level of aggregation should not matter; relationships should be stable across different levels (Land, McCall, and Cohen 1990). It remains possible, however, that using a different level of measurement would significantly alter the findings. This is particularly salient given that most criminological theory posits the mechanisms linking structural conditions to crime outcomes exist in the context of a “community” or “neighborhood.” It is difficult to imagine that a geographical space as large as a county or city would constitute such a frame of reference. Future research should attempt to estimate the relationships examined in this paper at a smaller aggregate while employing a similar analytic strategy, and care should be taken to use a nationally representative sample of units rather than limiting it to a particular city or metropolitan area as is common in past research.

Additionally, the current study only sampled counties categorized as SMSA components. The national trends in poverty and inequality discussed above do not appear to strictly apply to the current sample. Both relative and absolute deprivation appear to be fairly stable over time. As a result, the divergence of absolute and relative deprivation levels expected during the 1990-2000 period did not appear in this sample. This could be the result of moving beyond a single measure of absolute deprivation (i.e. poverty), the exclusion of non-metropolitan areas from the sample (if the decline in poverty levels at the national level was driven by decreases in non-metropolitan areas), or both. Future research should examine a wider array of areas and expand the examination of the deprivation/crime question to non-metropolitan aggregates, or perhaps analyze all U.S. counties with available data.

Overall, I am left to agree with the somewhat unsatisfying conclusion reached by Land et.al. (1990). The question of the comparative impact of absolute and relative deprivation on crime is an important one, not only for criminological theory, but for public policy as well. However, while these two formulations of “deprivation” are *conceptually* distinct, it appears extremely difficult to differentiate between them empirically. It is possible that given the strong relationship between the two types of deprivation, the question of which is more influential is moot, and researchers may simply combine the two into a single measure of “deprivation”

(Land, McCall, and Cohen 1990). I believe, however, that throwing in the towel on this question may be premature. Given the results of this study, particularly the differences between the cross-sectional and change-score analyses and the unforeseen negative relationship between relative deprivation and crime over time, more research in this area is clearly warranted. Employing more sophisticated research designs and using a more diverse sample of geographic areas may not only generate a clearer empirical understanding of the link between economic conditions and crime, but would also be an important step towards understanding the larger theoretical mechanisms connecting them.

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APPENDIX A – METROPOLITAN COMPONENTS

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
01001	Autauga County	Montgomery, AL
01003	Baldwin County	Mobile, AL
01009	Blount County	Birmingham, AL
01015	Calhoun County	Anniston, AL
01033	Colbert County	Florence, AL
01045	Dale County	Dothan, AL
01051	Elmore County	Montgomery, AL
01055	Etowah County	Gadsden, AL
01069	Houston County	Dothan, AL
01073	Jefferson County	Birmingham, AL
01077	Lauderdale County	Florence, AL
01079	Lawrence County	Decatur, AL
01089	Madison County	Huntsville, AL
01097	Mobile County	Mobile, AL
01101	Montgomery County	Montgomery, AL
01103	Morgan County	Decatur, AL
01113	Russell County, AL	Columbus, GA-AL
01115	St. Clair County	Birmingham, AL
01117	Shelby County	Birmingham, AL
01125	Tuscaloosa County	Tuscaloosa, AL
01127	Walker County	Birmingham, AL
02020	Anchorage Borough	Anchorage, AK
04013	Maricopa County	Phoenix, AZ
04019	Pima County	Tucson, AZ
04027	Yuma County	Yuma, AZ
05033	Crawford County, AR	Fort Smith, AR-OK
05035	Crittenden County, AR	Memphis, TN-AR-MS
05045	Faulkner County	Little Rock-North Little Rock, AR
05069	Jefferson County	Pine Bluff, AR
05085	Lonoke County	Little Rock-North Little Rock, AR
05091	Miller County, AR	Texarkana, TX-Texarkana, AR
05119	Pulaski County	Little Rock-North Little Rock, AR
05125	Saline County	Little Rock-North Little Rock, AR
05131	Sebastian County, AR	Fort Smith, AR-OK
05143	Washington County	Fayetteville-Springdale, AR
06001	Alameda County	Oakland, CA
06007	Butte County	Chico, CA
06013	Contra Costa County	Oakland, CA
06017	El Dorado County	Sacramento, CA
06019	Fresno County	Fresno, CA
06029	Kern County	Bakersfield, CA

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
06037	Los Angeles County	Los Angeles-Long Beach, CA
06041	Marin County	San Francisco, CA
06047	Merced County	Merced, CA
06053	Monterey County	Salinas-Seaside-Monterey, CA
06055	Napa County	Vallejo-Fairfield-Napa, CA
06059	Orange County	Anaheim-Santa Ana, CA
06061	Placer County	Sacramento, CA
06065	Riverside County	Riverside-San Bernardino, CA
06067	Sacramento County	Sacramento, CA
06071	San Bernardino County	Riverside-San Bernardino, CA
06073	San Diego County	San Diego, CA
06075	San Francisco County	San Francisco, CA
06077	San Joaquin County	Stockton, CA
06081	San Mateo County	San Francisco, CA
06083	Santa Barbara County	Santa Barbara-Santa Maria-Lompoc, CA
06085	Santa Clara County	San Jose, CA
06087	Santa Cruz County	Santa Cruz, CA
06089	Shasta County	Redding, CA
06095	Solano County	Vallejo-Fairfield-Napa, CA
06097	Sonoma County	Santa Rosa-Petaluma, CA
06099	Stanislaus County	Modesto, CA
06101	Sutter County	Yuba City, CA
06107	Tulare County	Visalia-Tulare-Porterville, CA
06111	Ventura County	Oxnard-Ventura, CA
06113	Yolo County	Sacramento, CA
06115	Yuba County	Yuba City, CA
08001	Adams County	Denver, CO
08005	Arapahoe County	Denver, CO
08013	Boulder County	Boulder-Longmont, CO
08031	Denver County	Denver, CO
08035	Douglas County	Denver, CO
08041	El Paso County	Colorado Springs, CO
08059	Jefferson County	Denver, CO
08069	Larimer County	Fort Collins-Loveland, CO
08101	Pueblo County	Pueblo, CO
08123	Weld County	Greeley, CO
10003	New Castle County, DE	Wilmington, DE-NJ-MD
11001	District of Columbia	Washington, DC-MD-VA
12001	Alachua County	Gainesville, FL
12005	Bay County	Panama City, FL
12007	Bradford County	Gainesville, FL
12009	Brevard County	Melbourne-Titusville-Palm Bay, FL
12011	Broward County	Fort Lauderdale-Hollywood-Pompano Beach, FL

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
12019	Clay County	Jacksonville, FL
12021	Collier County	Naples, FL
12025 (12086)	Miami-Dade County	Miami-Hialeah, FL
12031	Duval County	Jacksonville, FL
12033	Escambia County	Pensacola, FL
12039	Gadsden County	Tallahassee, FL
12053	Hernando County	Tampa-St. Petersburg-Clearwater, FL
12057	Hillsborough County	Tampa-St. Petersburg-Clearwater, FL
12071	Lee County	Fort Myers-Cape Coral, FL
12073	Leon County	Tallahassee, FL
12081	Manatee County	Bradenton, FL
12083	Marion County	Ocala, FL
12085	Martin County	Fort Pierce, FL
12089	Nassau County	Jacksonville, FL
12091	Okaloosa County	Fort Walton Beach, FL
12095	Orange County	Orlando, FL
12097	Osceola County	Orlando, FL
12099	Palm Beach County	West Palm Beach-Boca Raton-Delray Beach, FL
12101	Pasco County	Tampa-St. Petersburg-Clearwater, FL
12103	Pinellas County	Tampa-St. Petersburg-Clearwater, FL
12105	Polk County	Lakeland-Winter Haven, FL
12109	St. Johns County	Jacksonville, FL
12111	St. Lucie County	Fort Pierce, FL
12113	Santa Rosa County	Pensacola, FL
12115	Sarasota County	Sarasota, FL
12117	Seminole County	Orlando, FL
12127	Volusia County	Daytona Beach, FL
13013	Barrow County	Atlanta, GA
13021	Bibb County	Macon-Warner Robins, GA
13035	Butts County	Atlanta, GA
13047	Catoosa County, GA	Chattanooga, TN-GA
13051	Chatham County	Savannah, GA
13053	Chattahoochee County, GA	Columbus, GA-AL
13057	Cherokee County	Atlanta, GA
13059	Clarke County	Athens, GA
13063	Clayton County	Atlanta, GA
13067	Cobb County	Atlanta, GA
13073	Columbia County, GA	Augusta, GA-SC
13077	Coweta County	Atlanta, GA
13083	Dade County, GA	Chattanooga, TN-GA
13089	De Kalb County	Atlanta, GA
13095	Dougherty County	Albany, GA
13097	Douglas County	Atlanta, GA

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
13103	Effingham County	Savannah, GA
13113	Fayette County	Atlanta, GA
13117	Forsyth County	Atlanta, GA
13121	Fulton County	Atlanta, GA
13135	Gwinnett County	Atlanta, GA
13151	Henry County	Atlanta, GA
13153	Houston County	Macon-Warner Robins, GA
13157	Jackson County	Athens, GA
13169	Jones County	Macon-Warner Robins, GA
13177	Lee County	Albany, GA
13189	McDuffie County, GA	Augusta, GA-SC
13195	Madison County	Athens, GA
13215	Muscogee County, GA	Columbus, GA-AL
13217	Newton County	Atlanta, GA
13219	Oconee County	Athens, GA
13223	Paulding County	Atlanta, GA
13225	Peach County	Macon-Warner Robins, GA
13245	Richmond County, GA	Augusta, GA-SC
13247	Rockdale County	Atlanta, GA
13255	Spalding County	Atlanta, GA
13295	Walker County, GA	Chattanooga, TN-GA
13297	Walton County	Atlanta, GA
15003	Honolulu County	Honolulu, HI
16001	Ada County	Boise City, ID
17031	Cook County	Chicago, IL
17043	Du Page County	Chicago, IL
17089	Kane County	Aurora-Elgin, IL
17143	Peoria County	Peoria, IL
17167	Sangamon County	Springfield, IL
17197	Will County	Joliet, IL
17201	Winnebago County	Rockford, IL
18003	Allen County	Fort Wayne, IN
18011	Boone County	Indianapolis, IN
18019	Clark County, IN	Louisville, KY-IN
18021	Clay County	Terre Haute, IN
18033	De Kalb County	Fort Wayne, IN
18039	Elkhart County	Elkhart-Goshen, IN
18043	Floyd County, IN	Louisville, KY-IN
18057	Hamilton County	Indianapolis, IN
18059	Hancock County	Indianapolis, IN
18061	Harrison County, IN	Louisville, KY-IN
18063	Hendricks County	Indianapolis, IN
18067	Howard County	Kokomo, IN

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
18081	Johnson County	Indianapolis, IN
18089	Lake County	Gary-Hammond, IN
18095	Madison County	Anderson, IN
18097	Marion County	Indianapolis, IN
18105	Monroe County	Bloomington, IN
18109	Morgan County	Indianapolis, IN
18127	Porter County	Gary-Hammond, IN
18141	St. Joseph County	South Bend-Mishawaka, IN
18157	Tippecanoe County	Lafayette-West Lafayette, IN
18163	Vanderburgh County, IN	Evansville, IN-KY
18167	Vigo County	Terre Haute, IN
18173	Warrick County, IN	Evansville, IN-KY
19013	Black Hawk County	Waterloo-Cedar Falls, IA
19017	Bremer County	Waterloo-Cedar Falls, IA
19049	Dallas County	Des Moines, IA
19061	Dubuque County	Dubuque, IA
19103	Johnson County	Iowa City, IA
19113	Linn County	Cedar Rapids, IA
19153	Polk County	Des Moines, IA
19155	Pottawattamie County, IA	Omaha, NE-IA
19163	Scott County, IA	Davenport-Rock Island-Moline, IA-IL
19181	Warren County	Des Moines, IA
19193	Woodbury County, IA	Sioux City, IA-NE
20015	Butler County	Wichita, KS
20045	Douglas County	Lawrence, KS
20079	Harvey County	Wichita, KS
20091	Johnson County, KS	Kansas City, MO-KS
20103	Leavenworth County, KS	Kansas City, MO-KS
20121	Miami County, KS	Kansas City, MO-KS
20173	Sedgwick County	Wichita, KS
20177	Shawnee County	Topeka, KS
20209	Wyandotte County, KS	Kansas City, MO-KS
21015	Boone County, KY	Cincinnati, OH-KY-IN
21019	Boyd County, KY	Huntington-Ashland, WV-KY-OH
21037	Campbell County, KY	Cincinnati, OH-KY-IN
21059	Daviess County	Owensboro, KY
21067	Fayette County	Lexington-Fayette, KY
21111	Jefferson County, KY	Louisville, KY-IN
21239	Woodford County	Lexington-Fayette, KY
22005	Ascension Parish	Baton Rouge, LA
22015	Bossier Parish	Shreveport, LA
22017	Caddo Parish	Shreveport, LA
22019	Calcasieu Parish	Lake Charles, LA

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
22033	East Baton Rouge Parish	Baton Rouge, LA
22051	Jefferson Parish	New Orleans, LA
22055	Lafayette Parish	Lafayette, LA
22057	Lafourche Parish	Houma-Thibodaux, LA
22063	Livingston Parish	Baton Rouge, LA
22071	Orleans Parish	New Orleans, LA
22073	Ouachita Parish	Monroe, LA
22079	Rapides Parish	Alexandria, LA
22089	St. Charles Parish	New Orleans, LA
22095	St. John the Baptist Parish	New Orleans, LA
22099	St. Martin Parish	Lafayette, LA
22103	St. Tammany Parish	New Orleans, LA
22109	Terrebonne Parish	Houma-Thibodaux, LA
22121	West Baton Rouge Parish	Baton Rouge, LA
24001	Allegany County, MD	Cumberland, MD-WV
24003	Anne Arundel County	Baltimore, MD
24005	Baltimore County	Baltimore, MD
24009	Calvert County, MD	Washington, DC-MD-VA
24013	Carroll County	Baltimore, MD
24015	Cecil County, MD	Wilmington, DE-NJ-MD
24017	Charles County, MD	Washington, DC-MD-VA
24021	Frederick County, MD	Washington, DC-MD-VA
24025	Harford County	Baltimore, MD
24027	Howard County	Baltimore, MD
24031	Montgomery County, MD	Washington, DC-MD-VA
24033	Prince George's County, MD	Washington, DC-MD-VA
24035	Queen Anne's County	Baltimore, MD
24043	Washington County	Hagerstown, MD
24510	Baltimore city	Baltimore, MD
26017	Bay County	Saginaw-Bay City-Midland, MI
26021	Berrien County	Benton Harbor, MI
26025	Calhoun County	Battle Creek, MI
26037	Clinton County	Lansing-East Lansing, MI
26045	Eaton County	Lansing-East Lansing, MI
26049	Genesee County	Flint, MI
26065	Ingham County	Lansing-East Lansing, MI
26075	Jackson County	Jackson, MI
26077	Kalamazoo County	Kalamazoo, MI
26081	Kent County	Grand Rapids, MI
26087	Lapeer County	Detroit, MI
26093	Livingston County	Detroit, MI
26099	Macomb County	Detroit, MI
26111	Midland County	Saginaw-Bay City-Midland, MI

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
26115	Monroe County	Detroit, MI
26121	Muskegon County	Muskegon, MI
26125	Oakland County	Detroit, MI
26139	Ottawa County	Grand Rapids, MI
26145	Saginaw County	Saginaw-Bay City-Midland, MI
26147	St. Clair County	Detroit, MI
26161	Washtenaw County	Ann Arbor, MI
26163	Wayne County	Detroit, MI
27003	Anoka County, MN	Minneapolis-St. Paul, MN-WI
27009	Benton County	St. Cloud, MN
27019	Carver County, MN	Minneapolis-St. Paul, MN-WI
27025	Chisago County, MN	Minneapolis-St. Paul, MN-WI
27027	Clay County, MN	Fargo-Moorhead, ND-MN
27037	Dakota County, MN	Minneapolis-St. Paul, MN-WI
27053	Hennepin County, MN	Minneapolis-St. Paul, MN-WI
27059	Isanti County, MN	Minneapolis-St. Paul, MN-WI
27109	Olmsted County	Rochester, MN
27123	Ramsey County, MN	Minneapolis-St. Paul, MN-WI
27137	St. Louis County, MN	Duluth, MN-WI
27139	Scott County, MN	Minneapolis-St. Paul, MN-WI
27141	Sherburne County	St. Cloud, MN
27145	Stearns County	St. Cloud, MN
27163	Washington County, MN	Minneapolis-St. Paul, MN-WI
27171	Wright County, MN	Minneapolis-St. Paul, MN-WI
28033	De Soto County, MS	Memphis, TN-AR-MS
28045	Hancock County	Biloxi-Gulfport, MS
28047	Harrison County	Biloxi-Gulfport, MS
28049	Hinds County	Jackson, MS
28059	Jackson County	Pascagoula, MS
28089	Madison County	Jackson, MS
28121	Rankin County	Jackson, MS
29019	Boone County	Columbia, MO
29021	Buchanan County	St. Joseph, MO
29037	Cass County, MO	Kansas City, MO-KS
29043	Christian County	Springfield, MO
29047	Clay County, MO	Kansas City, MO-KS
29071	Franklin County, MO	St. Louis, MO-IL
29077	Greene County	Springfield, MO
29095	Jackson County, MO	Kansas City, MO-KS
29097	Jasper County	Joplin, MO
29099	Jefferson County, MO	St. Louis, MO-IL
29107	Lafayette County, MO	Kansas City, MO-KS
29145	Newton County	Joplin, MO

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
29165	Platte County, MO	Kansas City, MO-KS
29177	Ray County, MO	Kansas City, MO-KS
29183	St. Charles County, MO	St. Louis, MO-IL
29189	St. Louis County, MO	St. Louis, MO-IL
29510	St. Louis city, MO	St. Louis, MO-IL
30013	Cascade County	Great Falls, MT
30111	Yellowstone County	Billings, MT
31043	Dakota County, NE	Sioux City, IA-NE
31055	Douglas County, NE	Omaha, NE-IA
31109	Lancaster County	Lincoln, NE
31153	Sarpy County, NE	Omaha, NE-IA
31177	Washington County, NE	Omaha, NE-IA
32003	Clark County	Las Vegas, NV
32031	Washoe County	Reno, NV
34001	Atlantic County	Atlantic City, NJ
34003	Bergen County	Bergen-Passaic, NJ
34005	Burlington County, NJ	Philadelphia, PA-NJ
34007	Camden County, NJ	Philadelphia, PA-NJ
34009	Cape May County	Atlantic City, NJ
34011	Cumberland County	Vineland-Millville-Bridgeton, NJ
34013	Essex County	Newark, NJ
34015	Gloucester County, NJ	Philadelphia, PA-NJ
34017	Hudson County	Jersey City, NJ
34019	Hunterdon County	Middlesex-Somerset-Hunterdon, NJ
34021	Mercer County	Trenton, NJ
34023	Middlesex County	Middlesex-Somerset-Hunterdon, NJ
34025	Monmouth County	Monmouth-Ocean, NJ
34027	Morris County	Newark, NJ
34029	Ocean County	Monmouth-Ocean, NJ
34031	Passaic County	Bergen-Passaic, NJ
34033	Salem County, NJ	Wilmington, DE-NJ-MD
34035	Somerset County	Middlesex-Somerset-Hunterdon, NJ
34037	Sussex County	Newark, NJ
34039	Union County	Newark, NJ
34041	Warren County, NJ	Allentown-Bethlehem-Easton, PA-NJ
35001	Bernalillo County	Albuquerque, NM
35013	Dona Ana County	Las Cruces, NM
35028	Los Alamos County	Santa Fe, NM
35049	Santa Fe County	Santa Fe, NM
36001	Albany County	Albany-Schenectady-Troy, NY
36005	Bronx County	New York, NY
36007	Broome County	Binghamton, NY
36013	Chautauqua County	Jamestown-Dunkirk, NY

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
36015	Chemung County	Elmira, NY
36027	Dutchess County	Poughkeepsie, NY
36029	Erie County	Buffalo, NY
36039	Greene County	Albany-Schenectady-Troy, NY
36043	Herkimer County	Utica-Rome, NY
36047	Kings County	New York, NY
36051	Livingston County	Rochester, NY
36053	Madison County	Syracuse, NY
36055	Monroe County	Rochester, NY
36057	Montgomery County	Albany-Schenectady-Troy, NY
36059	Nassau County	Nassau-Suffolk, NY
36061	New York County	New York, NY
36063	Niagara County	Niagara Falls, NY
36065	Oneida County	Utica-Rome, NY
36067	Onondaga County	Syracuse, NY
36069	Ontario County	Rochester, NY
36071	Orange County	Orange County, NY
36073	Orleans County	Rochester, NY
36075	Oswego County	Syracuse, NY
36079	Putnam County	New York, NY
36081	Queens County	New York, NY
36083	Rensselaer County	Albany-Schenectady-Troy, NY
36085	Richmond County	New York, NY
36087	Rockland County	New York, NY
36091	Saratoga County	Albany-Schenectady-Troy, NY
36093	Schenectady County	Albany-Schenectady-Troy, NY
36103	Suffolk County	Nassau-Suffolk, NY
36107	Tioga County	Binghamton, NY
36113	Warren County	Glens Falls, NY
36115	Washington County	Glens Falls, NY
36117	Wayne County	Rochester, NY
36119	Westchester County	New York, NY
37001	Alamance County	Burlington, NC
37003	Alexander County	Hickory-Morganton, NC
37021	Buncombe County	Asheville, NC
37023	Burke County	Hickory-Morganton, NC
37025	Cabarrus County, NC	Charlotte-Gastonia-Rock Hill, NC-SC
37035	Catawba County	Hickory-Morganton, NC
37051	Cumberland County	Fayetteville, NC
37057	Davidson County	Greensboro--Winston-Salem--High Point, NC
37059	Davie County	Greensboro--Winston-Salem--High Point, NC
37063	Durham County	Raleigh-Durham, NC
37067	Forsyth County	Greensboro--Winston-Salem--High Point, NC

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
37069	Franklin County	Raleigh-Durham, NC
37071	Gaston County, NC	Charlotte-Gastonia-Rock Hill, NC-SC
37081	Guilford County	Greensboro--Winston-Salem--High Point, NC
37109	Lincoln County, NC	Charlotte-Gastonia-Rock Hill, NC-SC
37119	Mecklenburg County, NC	Charlotte-Gastonia-Rock Hill, NC-SC
37129	New Hanover County	Wilmington, NC
37133	Onslow County	Jacksonville, NC
37135	Orange County	Raleigh-Durham, NC
37151	Randolph County	Greensboro--Winston-Salem--High Point, NC
37159	Rowan County, NC	Charlotte-Gastonia-Rock Hill, NC-SC
37169	Stokes County	Greensboro--Winston-Salem--High Point, NC
37179	Union County, NC	Charlotte-Gastonia-Rock Hill, NC-SC
37183	Wake County	Raleigh-Durham, NC
37197	Yadkin County	Greensboro--Winston-Salem--High Point, NC
38015	Burleigh County	Bismarck, ND
38017	Cass County, ND	Fargo-Moorhead, ND-MN
38035	Grand Forks County	Grand Forks, ND
38059	Morton County	Bismarck, ND
39003	Allen County	Lima, OH
39011	Auglaize County	Lima, OH
39013	Belmont County, OH	Wheeling, WV-OH
39017	Butler County	Hamilton-Middletown, OH
39019	Carroll County	Canton, OH
39023	Clark County	Dayton-Springfield, OH
39025	Clermont County, OH	Cincinnati, OH-KY-IN
39035	Cuyahoga County	Cleveland, OH
39041	Delaware County	Columbus, OH
39045	Fairfield County	Columbus, OH
39049	Franklin County	Columbus, OH
39051	Fulton County	Toledo, OH
39055	Geauga County	Cleveland, OH
39057	Greene County	Dayton-Springfield, OH
39061	Hamilton County, OH	Cincinnati, OH-KY-IN
39081	Jefferson County, OH	Steubenville-Weirton, OH-WV
39085	Lake County	Cleveland, OH
39089	Licking County	Columbus, OH
39093	Lorain County	Lorain-Elyria, OH
39095	Lucas County	Toledo, OH
39097	Madison County	Columbus, OH
39099	Mahoning County	Youngstown-Warren, OH
39103	Medina County	Cleveland, OH
39109	Miami County	Dayton-Springfield, OH
39113	Montgomery County	Dayton-Springfield, OH

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
39129	Pickaway County	Columbus, OH
39133	Portage County	Akron, OH
39139	Richland County	Mansfield, OH
39151	Stark County	Canton, OH
39153	Summit County	Akron, OH
39155	Trumbull County	Youngstown-Warren, OH
39159	Union County	Columbus, OH
39165	Warren County, OH	Cincinnati, OH-KY-IN
39167	Washington County, OH	Parkersburg-Marietta, WV-OH
39173	Wood County	Toledo, OH
40017	Canadian County	Oklahoma City, OK
40027	Cleveland County	Oklahoma City, OK
40031	Comanche County	Lawton, OK
40037	Creek County	Tulsa, OK
40047	Garfield County	Enid, OK
40083	Logan County	Oklahoma City, OK
40087	McClain County	Oklahoma City, OK
40109	Oklahoma County	Oklahoma City, OK
40113	Osage County	Tulsa, OK
40125	Pottawatomie County	Oklahoma City, OK
40131	Rogers County	Tulsa, OK
40135	Sequoyah County, OK	Fort Smith, AR-OK
40143	Tulsa County	Tulsa, OK
40145	Wagoner County	Tulsa, OK
41005	Clackamas County	Portland, OR
41029	Jackson County	Medford, OR
41039	Lane County	Eugene-Springfield, OR
41047	Marion County	Salem, OR
41051	Multnomah County	Portland, OR
41053	Polk County	Salem, OR
41067	Washington County	Portland, OR
41071	Yamhill County	Portland, OR
42001	Adams County	York, PA
42003	Allegheny County	Pittsburgh, PA
42007	Beaver County	Beaver County, PA
42011	Berks County	Reading, PA
42013	Blair County	Altoona, PA
42017	Bucks County, PA	Philadelphia, PA-NJ
42021	Cambria County	Johnstown, PA
42025	Carbon County, PA	Allentown-Bethlehem-Easton, PA-NJ
42027	Centre County	State College, PA
42029	Chester County, PA	Philadelphia, PA-NJ
42037	Columbia County	Scranton--Wilkes-Barre, PA

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
42041	Cumberland County	Harrisburg-Lebanon-Carlisle, PA
42043	Dauphin County	Harrisburg-Lebanon-Carlisle, PA
42045	Delaware County, PA	Philadelphia, PA-NJ
42049	Erie County	Erie, PA
42051	Fayette County	Pittsburgh, PA
42069	Lackawanna County	Scranton--Wilkes-Barre, PA
42071	Lancaster County	Lancaster, PA
42075	Lebanon County	Harrisburg-Lebanon-Carlisle, PA
42077	Lehigh County, PA	Allentown-Bethlehem-Easton, PA-NJ
42079	Luzerne County	Scranton--Wilkes-Barre, PA
42081	Lycoming County	Williamsport, PA
42085	Mercer County	Sharon, PA
42089	Monroe County	Scranton--Wilkes-Barre, PA
42091	Montgomery County, PA	Philadelphia, PA-NJ
42095	Northampton County, PA	Allentown-Bethlehem-Easton, PA-NJ
42099	Perry County	Harrisburg-Lebanon-Carlisle, PA
42101	Philadelphia County, PA	Philadelphia, PA-NJ
42111	Somerset County	Johnstown, PA
42125	Washington County	Pittsburgh, PA
42129	Westmoreland County	Pittsburgh, PA
42131	Wyoming County	Scranton--Wilkes-Barre, PA
42133	York County	York, PA
45003	Aiken County, SC	Augusta, GA-SC
45007	Anderson County	Anderson, SC
45015	Berkeley County	Charleston, SC
45019	Charleston County	Charleston, SC
45035	Dorchester County	Charleston, SC
45041	Florence County	Florence, SC
45045	Greenville County	Greenville-Spartanburg, SC
45063	Lexington County	Columbia, SC
45077	Pickens County	Greenville-Spartanburg, SC
45079	Richland County	Columbia, SC
45083	Spartanburg County	Greenville-Spartanburg, SC
45091	York County, SC	Charlotte-Gastonia-Rock Hill, NC-SC
46099	Minnehaha County	Sioux Falls, SD
46103	Pennington County	Rapid City, SD
47001	Anderson County	Knoxville, TN
47009	Blount County	Knoxville, TN
47019	Carter County, TN	Johnson City-Kingsport-Bristol, TN-VA
47021	Cheatham County	Nashville, TN
47037	Davidson County	Nashville, TN
47043	Dickson County	Nashville, TN
47057	Grainger County	Knoxville, TN

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
47065	Hamilton County, TN	Chattanooga, TN-GA
47073	Hawkins County, TN	Johnson City-Kingsport-Bristol, TN-VA
47089	Jefferson County	Knoxville, TN
47093	Knox County	Knoxville, TN
47113	Madison County	Jackson, TN
47115	Marion County, TN	Chattanooga, TN-GA
47125	Montgomery County, TN	Clarksville-Hopkinsville, TN-KY
47147	Robertson County	Nashville, TN
47149	Rutherford County	Nashville, TN
47155	Sevier County	Knoxville, TN
47157	Shelby County, TN	Memphis, TN-AR-MS
47163	Sullivan County, TN	Johnson City-Kingsport-Bristol, TN-VA
47165	Sumner County	Nashville, TN
47171	Unicoi County, TN	Johnson City-Kingsport-Bristol, TN-VA
47173	Union County	Knoxville, TN
47179	Washington County, TN	Johnson City-Kingsport-Bristol, TN-VA
47187	Williamson County	Nashville, TN
47189	Wilson County	Nashville, TN
48027	Bell County	Killeen-Temple, TX
48029	Bexar County	San Antonio, TX
48037	Bowie County, TX	Texarkana, TX-Texarkana, AR
48039	Brazoria County	Brazoria, TX
48041	Brazos County	Bryan-College Station, TX
48061	Cameron County	Brownsville-Harlingen, TX
48085	Collin County	Dallas, TX
48091	Comal County	San Antonio, TX
48099	Coryell County	Killeen-Temple, TX
48113	Dallas County	Dallas, TX
48121	Denton County	Dallas, TX
48135	Ector County	Odessa, TX
48139	Ellis County	Dallas, TX
48141	El Paso County	El Paso, TX
48157	Fort Bend County	Houston, TX
48167	Galveston County	Galveston-Texas City, TX
48181	Grayson County	Sherman-Denison, TX
48183	Gregg County	Longview-Marshall, TX
48187	Guadalupe County	San Antonio, TX
48199	Hardin County	Beaumont-Port Arthur, TX
48201	Harris County	Houston, TX
48203	Harrison County	Longview-Marshall, TX
48209	Hays County	Austin, TX
48215	Hidalgo County	McAllen-Edinburg-Mission, TX
48245	Jefferson County	Beaumont-Port Arthur, TX

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
48251	Johnson County	Fort Worth-Arlington, TX
48257	Kaufman County	Dallas, TX
48291	Liberty County	Houston, TX
48303	Lubbock County	Lubbock, TX
48309	McLennan County	Waco, TX
48329	Midland County	Midland, TX
48339	Montgomery County	Houston, TX
48355	Nueces County	Corpus Christi, TX
48361	Orange County	Beaumont-Port Arthur, TX
48367	Parker County	Fort Worth-Arlington, TX
48375	Potter County	Amarillo, TX
48381	Randall County	Amarillo, TX
48397	Rockwall County	Dallas, TX
48409	San Patricio County	Corpus Christi, TX
48423	Smith County	Tyler, TX
48439	Tarrant County	Fort Worth-Arlington, TX
48441	Taylor County	Abilene, TX
48451	Tom Green County	San Angelo, TX
48453	Travis County	Austin, TX
48469	Victoria County	Victoria, TX
48473	Waller County	Houston, TX
48479	Webb County	Laredo, TX
48485	Wichita County	Wichita Falls, TX
48491	Williamson County	Austin, TX
49011	Davis County	Salt Lake City-Ogden, UT
49035	Salt Lake County	Salt Lake City-Ogden, UT
49049	Utah County	Provo-Orem, UT
49057	Weber County	Salt Lake City-Ogden, UT
51003	Albemarle County	Charlottesville, VA
51009	Amherst County	Lynchburg, VA
51013	Arlington County, VA	Washington, DC-MD-VA
51023	Botetourt County	Roanoke, VA
51031	Campbell County	Lynchburg, VA
51036	Charles City County	Richmond-Petersburg, VA
51041	Chesterfield County	Richmond-Petersburg, VA
51053	Dinwiddie County	Richmond-Petersburg, VA
51059	Fairfax County, VA	Washington, DC-MD-VA
51065	Fluvanna County	Charlottesville, VA
51073	Gloucester County	Norfolk-Virginia Beach-Newport News, VA
51075	Goochland County	Richmond-Petersburg, VA
51079	Greene County	Charlottesville, VA
51085	Hanover County	Richmond-Petersburg, VA
51087	Henrico County	Richmond-Petersburg, VA

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
51095	James City County	Norfolk-Virginia Beach-Newport News, VA
51107	Loudoun County, VA	Washington, DC-MD-VA
51127	New Kent County	Richmond-Petersburg, VA
51143	Pittsylvania County	Danville, VA
51145	Powhatan County	Richmond-Petersburg, VA
51149	Prince George County	Richmond-Petersburg, VA
51153	Prince William County, VA	Washington, DC-MD-VA
51161	Roanoke County	Roanoke, VA
51169	Scott County, VA	Johnson City-Kingsport-Bristol, TN-VA
51179	Stafford County, VA	Washington, DC-MD-VA
51191	Washington County, VA	Johnson City-Kingsport-Bristol, TN-VA
51199	York County	Norfolk-Virginia Beach-Newport News, VA
51510	Alexandria city, VA	Washington, DC-MD-VA
51520	Bristol city, VA	Johnson City-Kingsport-Bristol, TN-VA
51540	Charlottesville city	Charlottesville, VA
51550	Chesapeake city	Norfolk-Virginia Beach-Newport News, VA
51570	Colonial Heights city	Richmond-Petersburg, VA
51590	Danville city	Danville, VA
51600	Fairfax city, VA	Washington, DC-MD-VA
51610	Falls Church city, VA	Washington, DC-MD-VA
51650	Hampton city	Norfolk-Virginia Beach-Newport News, VA
51670	Hopewell city	Richmond-Petersburg, VA
51680	Lynchburg city	Lynchburg, VA
51683	Manassas city, VA	Washington, DC-MD-VA
51685	Manassas Park city, VA	Washington, DC-MD-VA
51700	Newport News city	Norfolk-Virginia Beach-Newport News, VA
51710	Norfolk city	Norfolk-Virginia Beach-Newport News, VA
51730	Petersburg city	Richmond-Petersburg, VA
51735	Poquoson city	Norfolk-Virginia Beach-Newport News, VA
51740	Portsmouth city	Norfolk-Virginia Beach-Newport News, VA
51760	Richmond city	Richmond-Petersburg, VA
51770	Roanoke city	Roanoke, VA
51775	Salem city	Roanoke, VA
51800	Suffolk city	Norfolk-Virginia Beach-Newport News, VA
51810	Virginia Beach city	Norfolk-Virginia Beach-Newport News, VA
51830	Williamsburg city	Norfolk-Virginia Beach-Newport News, VA
53005	Benton County	Richland-Kennewick-Pasco, WA
53011	Clark County	Vancouver, WA
53021	Franklin County	Richland-Kennewick-Pasco, WA
53033	King County	Seattle, WA
53035	Kitsap County	Bremerton, WA
53053	Pierce County	Tacoma, WA
53061	Snohomish County	Seattle, WA

FIPS	COUNTY/CITY	(PRIMARY) METROPOLITAN AREA
53063	Spokane County	Spokane, WA
53067	Thurston County	Olympia, WA
53073	Whatcom County	Bellingham, WA
53077	Yakima County	Yakima, WA
54009	Brooke County, WV	Steubenville-Weirton, OH-WV
54011	Cabell County, WV	Huntington-Ashland, WV-KY-OH
54029	Hancock County, WV	Steubenville-Weirton, OH-WV
54039	Kanawha County	Charleston, WV
54051	Marshall County, WV	Wheeling, WV-OH
54057	Mineral County, WV	Cumberland, MD-WV
54069	Ohio County, WV	Wheeling, WV-OH
54079	Putnam County	Charleston, WV
54099	Wayne County, WV	Huntington-Ashland, WV-KY-OH
54107	Wood County, WV	Parkersburg-Marietta, WV-OH
55009	Brown County	Green Bay, WI
55015	Calumet County	Appleton-Oshkosh-Neenah, WI
55017	Chippewa County	Eau Claire, WI
55025	Dane County	Madison, WI
55031	Douglas County, WI	Duluth, MN-WI
55035	Eau Claire County	Eau Claire, WI
55059	Kenosha County	Kenosha, WI
55063	La Crosse County	La Crosse, WI
55073	Marathon County	Wausau, WI
55079	Milwaukee County	Milwaukee, WI
55087	Outagamie County	Appleton-Oshkosh-Neenah, WI
55089	Ozaukee County	Milwaukee, WI
55101	Racine County	Racine, WI
55105	Rock County	Janesville-Beloit, WI
55109	St. Croix County, WI	Minneapolis-St. Paul, MN-WI
55117	Sheboygan County	Sheboygan, WI
55131	Washington County	Milwaukee, WI
55133	Waukesha County	Milwaukee, WI
55139	Winnebago County	Appleton-Oshkosh-Neenah, WI
56021	Laramie County	Cheyenne, WY
56025	Natrona County	Casper, WY

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 of four outcome variables (total crime rate, property crime rate, violent crime rate, and homicide rate) were calculated. Below are the definitions of the seven crimes used to construct the 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.

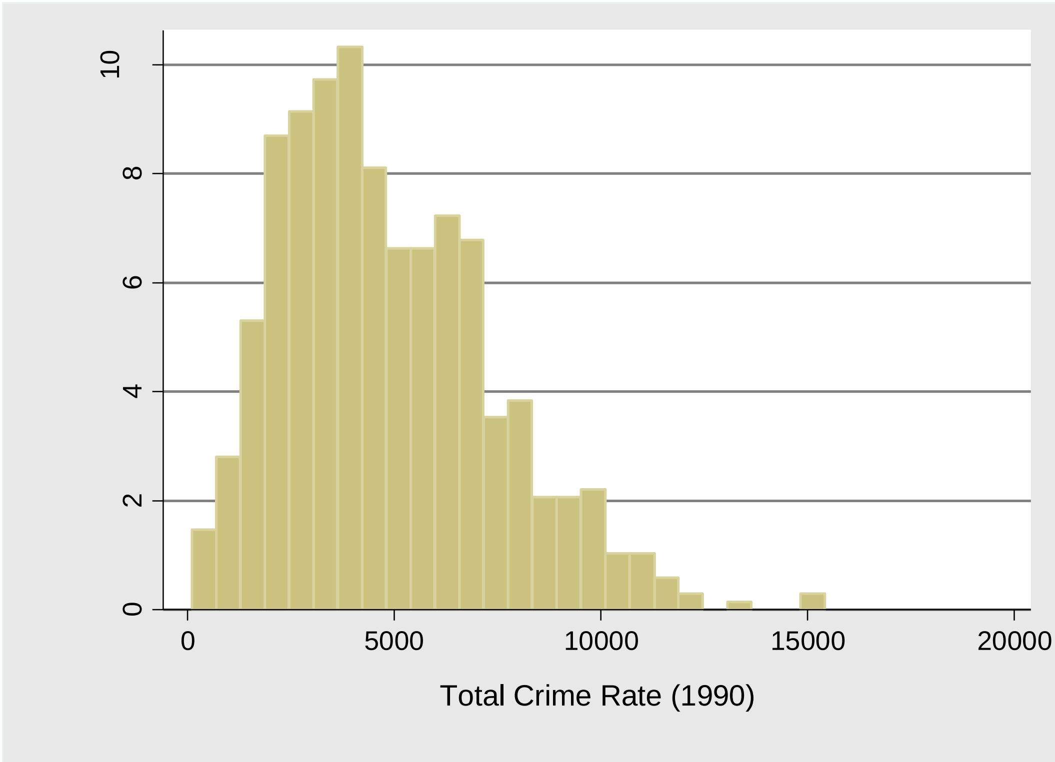
Aggravated assault — An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm. Simple assaults are excluded.

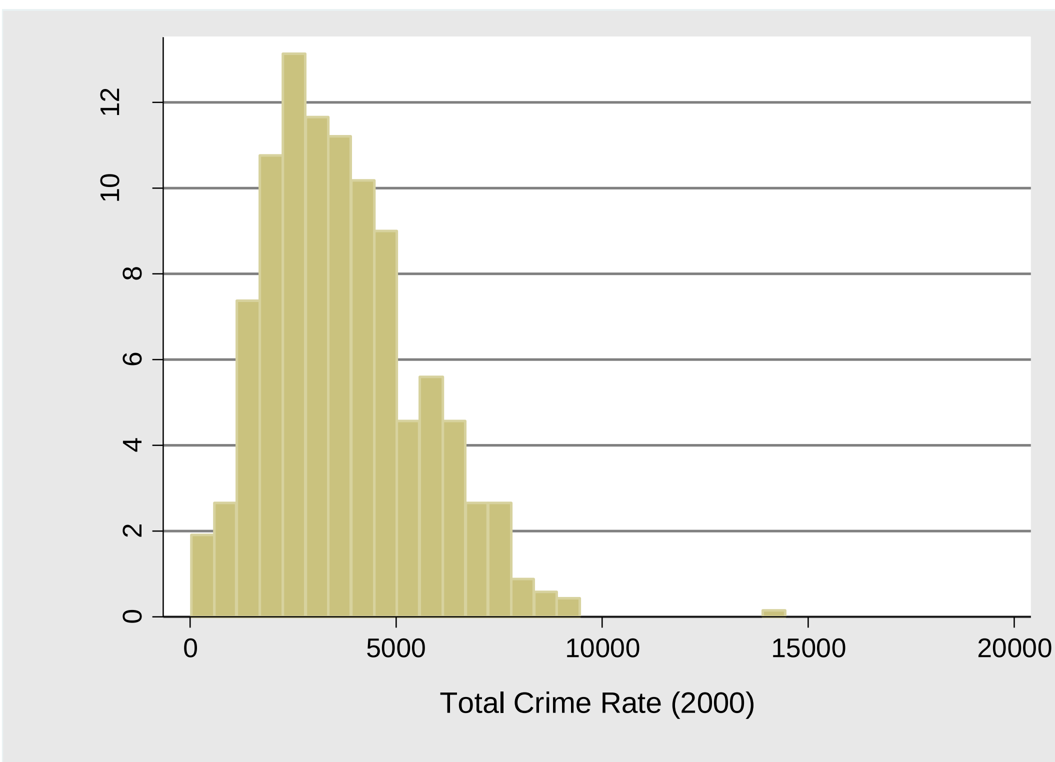
Burglary — The unlawful entry of a structure to commit a felony or a theft. Attempted forcible entry is included.

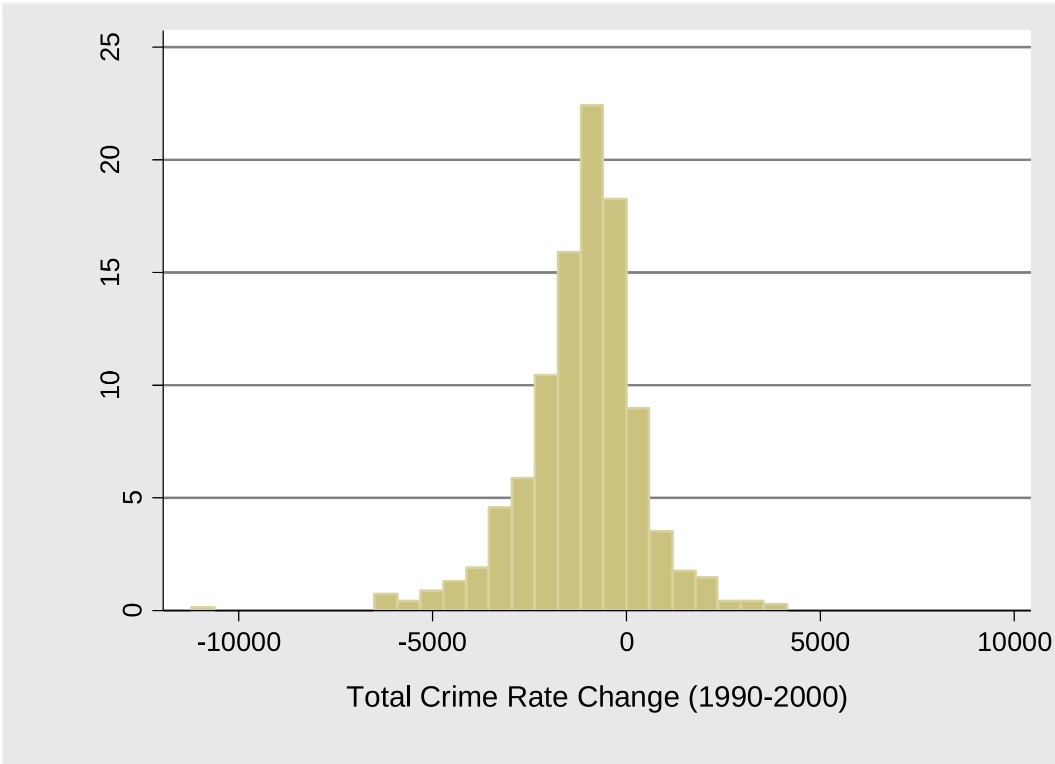
Larceny-theft (except motor vehicle theft) — The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. Examples are thefts of bicycles, motor vehicle parts and accessories, shoplifting, pocket-picking, or the stealing of any property 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.

APPENDIX C – TOTAL CRIME DISTRIBUTIONS






25
20
15
10
5
0
-10000
-5000
0
5000
10000
Total Crime Rate Change (1990-2000)

APPENDIX D – INDEPENDENT AND CONTROL VARIABLES

The independent and control 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 11 independent and control variables from Census data categories for each metropolitan statistical area component.

Absolute deprivation – four highly correlated census variables were combined into a single principal-component rotated factor-weighted variable using STATA; the definitions of the census variables included in this factor measure are:

> **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
>
> **Female head of household, no husband present, with children** – the number of family households with children headed by females, with no husband present, divided by the total number of family households with children
>
> **High-school graduates** – 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

Relative deprivation (the Gini index of income inequality) – 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)[1], Gini coefficients were calculated for each metropolitan statistical area component.

Total population – the total number of residents

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

Young adults – the population between the ages of 18 and 24 divided by the total population

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

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[1] STATA code from this equation was produced by Stephen P. Jenkins and available at http://econpapers.repec.org/paper/bocasug06/16.htm

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

Residential stability – 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

Hispanic – the population of Hispanic-ethnicity residents divided by the total population

Foreign-born – the population of foreign-born residents divided by the total population

Racial heterogeneity - An entropy measure of the 3-group (black, white, and other) index score calculated for each unit; the entropy index (E) is a multi-group measure of the diversity of a geographic area, calculated as:

$$E = \sum_{m=1}^{M} \pi_m \ln(1/\pi_m)$$

where π_m is the proportion of people in race m (e.g., proportion black) and M is the total number of racial groups. E has a minimum value of 0 when a census unit has no diversity and is composed entirely of one racial group and a maximum value of 1 when blacks, whites, and other are equally represented. Racial heterogeneity scores were divided by their maximum values in 1990 and 2000 (roughly 1.09) to impose a range of 0 to 1 for E.

APPENDIX E – SUPPLEMENTAL POVERTY-HOMICIDE (1990) ANALYSIS

Table 15. Supplemental OLS Regression of 1990 Homicide UCR Offenses (logged) on Poverty (N = 678)

	Model 1				Model 2				Model 3				Model 4				Model 5			
	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta	b		(SE)	Beta
Below poverty	6.56	**	(0.46)	0.48	-		-	-	3.32	**	0.76	0.24	0.18		0.95	0.01	2.68	**	0.71	0.20
Relative deprivation	-		-	-	11.22	**	(0.77)	0.49	6.77	**	1.27	0.29	1.66		1.06	0.07	2.07	*	1.05	0.09
Female head of household	-		-	-	-		-	-	-		-	-	3.12	**	0.59	0.27	-		-	-
High-school graduates	-		-	-	-		-	-	-		-	-	-1.86	**	0.37	-0.20	-		-	-
Unemployed	-		-	-	-		-	-	-		-	-	-2.70		2.78	-0.04	-		-	-
Total population (ln)	-		-	-	-		-	-	-		-	-	0.10	**	0.02	0.14	0.09	**	0.02	0.14
Urbanization	-		-	-	-		-	-	-		-	-	-0.11		0.12	-0.04	-0.20		0.11	-0.07
Young adults	-		-	-	-		-	-	-		-	-	-3.85	**	0.71	-0.18	-5.45	**	0.68	-0.25
Vacant housing	-		-	-	-		-	-	-		-	-	1.14	**	0.41	0.07	1.30	**	0.42	0.08
Owner-occupied housing	-		-	-	-		-	-	-		-	-	-0.42		0.40	-0.05	-1.37	**	0.37	-0.18
Residential stability	-		-	-	-		-	-	-		-	-	-1.00	**	0.32	-0.11	-0.11		0.30	-0.01
Hispanic	-		-	-	-		-	-	-		-	-	-0.06		0.30	-0.01	-0.56		0.29	-0.07
Foreign-born	-		-	-	-		-	-	-		-	-	-1.42	*	0.58	-0.10	-1.89	**	0.59	-0.13
Racial heterogeneity	-		-	-	-		-	-	-		-	-	1.69	**	0.13	0.47	2.17	**	0.12	0.61
Constant	0.94	**	(0.06)		-2.79	**	(0.31)		-1.40	**	0.44		1.44	*	0.62		0.37	**	0.54	
R^2	0.23				0.24				0.14				0.67				0.64			

*p<.05 **p<.01

To counter criticisms regarding the use of a multi-item factor measure of absolute deprivation in place of the single-item poverty measure typically used, a supplemental analysis was conducted to compare the relationships between poverty and homicide to those between absolute deprivation (the factor measure) and homicide in 1990. This analysis supports the use of a multi-item measure of absolute deprivation. Not only is the correlation between the two primary independent variables reduced, but the multicollinearity between poverty, relative deprivation, and several control variables is eliminated. The poverty-only measure of absolute deprivation displays a relationship with homicide that is very similar to the one found above between the factor measure and homicide. Table 15 displays the results of the analysis. In Model 1, poverty alone is included as a predictor of homicide. The significant relationship is in the expected positive direction, approximating the relationship between absolute deprivation and homicide. The relationship between relative inequality as the sole predictor and homicide in Model 2 is identical to the earlier analysis. When both types of deprivation are included together without controls, each is significantly related to homicide in the expected positive direction. The size of the poverty coefficient (b = 3.32) is substantially smaller than in Model 1, while the standard error (SE = .76) is substantially larger. Both differences are likely due to the strong correlation between the relative deprivation measure and poverty (R = .80) and indicative of the problems collinearity introduces into estimates. Model 4 is the "full" model for this analysis. In addition to the set of controls discussed in the text, it also includes the three variables which were combined into the factor-measure of absolute deprivation: the proportions of female-headed households, high-school graduates, and unemployed. Unlike the previous full model of homicide in 1990 (Table 6), neither poverty nor relative deprivation is significantly related to the outcome, though the relationships are still positive. This is likely due to high multicollinearity between variables (as evidenced by the factor loadings earlier). The poverty coefficient (b = .18) is substantially reduced and the standard error (SE = .95) is much larger than in Model 3. In other words, the amount of unique variance attributable to poverty is very small and unrelated to homicide due to multicollinearity. This interpretation is supported by Model 5, which does not use the expanded set of control variables. Both deprivation variables are now significantly and positively related to homicide, and the coefficient (b = 2.68) and standard error (SE = .71) of poverty are much closer to those in Model 3. In addition, poverty has a much larger standardized effect (Beta = .20) than relative deprivation (Beta = .09) on poverty, paralleling the analysis using the factor measure.