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## Social Disorganization Outside the Metropolis:

## An Analysis of Rural Youth Violence

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In order to extend the study of community social disorganization and crime beyond its exclusive focus on large urban centers, we present an analysis of structural correlates of arrest rates for juvenile violence in 264 non-metropolitan counties of four states. Findings support the generality of social disorganization theory: Juvenile violence was associated with rates of residential instability, family disruption, and ethnic heterogeneity. Though rates of poverty were not related to juvenile violence, this is also in accord with social disorganization theory because, unlike urban settings, poverty was negatively related to residential instability. Rates of juvenile violence varied markedly with population size through a curvilinear relationship in which counties with the smallest juvenile populations had exceptionally low arrest rates.

Analyses used negative binomial regression (a variation of Poisson regression) because there were few arrests in many counties and arrest rates would be ill suited to least squares regression.

# Social Disorganization Outside the Metropolis:

# An Analysis of Rural Youth Violence

This paper extends the study of community social disorganization and crime to non-metropolitan settings. Our purpose is to assess the generalizability to this setting of the social disorganization theory of crime that has been developed and tested in urban communities. In doing so we test the proposition that social disorganization theory is based on principles of community organization and social relations that are applicable to communities of all types and settings.

Research on the contribution of community context to rates of crime and delinquency is not only a tradition of long standing in criminology, but it is also a very active area of research today. Growing out of the Chicago school of sociology's emphasis on urban ecology (Burgess, 1925; Park & Burgess, 1924; Shaw and McKay, 1942; Thrasher, 1927), theory and research on crime and communities has almost exclusively defined communities as neighborhoods within large urban centers.<sup>1</sup>

Yet according to the 1990 census (United States Department of Commerce, 1992), only 49% of the U.S. population lives in urbanized areas of 500,000 or more, while 25% lives in fully rural settings (i.e., places with population of no more than 2,500) and another 12% lives in towns or cities of under 50,000 population. Though overall crime rates are higher in urban than rural areas (e.g., Maguire and Pastore, 1995: 316-317), this difference is not as large as is widely assumed, and there is considerable variation in crime rates among small towns and rural areas.

Several authors have called for more attention to crime in rural settings (e.g., Smith and Huff, 1982; Swanson, 1981; Weisheit, Wells, & Falcone, 1995). Though these authors document that rural settings have unique crime problems (e.g., agriculture crime), they also

review striking evidence of similarity between urban and rural settings for the patterning of crime in relation to important factors such as time, age, sex, and race (e.g., Bachman, 1992; Laub 1983a, 1983b). Such findings led Laub (1983b) to conclude that most theories of crime and delinquency are likely to apply to rural settings, even though they were developed in reference to urban settings. Laub's discussion primarily concerned individual level theories of crime, but his point is especially interesting for community level theories. The rural-urban dimension is itself an essential aspect of communities, and our current theories of communities and crime would be far more useful if they apply to the entire range of this dimension. Indeed, if the study of communities and crime is to mature, it must expand to encompass the full variety of communities. Toward that end, we present a county level analysis of youth violence that tests whether the most prominent theory in this area, social disorganization theory, is applicable to non-metropolitan communities.

# SOCIAL DISORGANIZATION RESEARCH AND RURAL COMMUNITIES

As was typical of the progressive era philosophy from which the Chicago school grew, its members believed that major social problems such as crime stemmed from the disruption of the social fabric that occurred with massive population shifts from rural to urban areas (e.g., Bursik and Grasmick, 1993: 165). Shaw and McKay's (1942) now classic theory portrays delinquency as arising from social disorganization, which is an inability of community members to achieve shared values or to solve jointly experienced problems (Bursik, 1988).

Shaw and McKay traced social disorganization to conditions endemic in the urban areas where the newly arriving poor were forced to settle, especially residential instability and ethnic heterogeneity. Here Shaw and McKay were building on notions of community solidarity and disorganization that were first developed by fellow members of the Chicago School, Thomas and Znaniecki (1958 [1927]), in their classic study of Polish peasants. Shaw

and McKay's analyses relating delinquency rates to these structural characteristics spawned an enduring line of research. In the past twenty years the themes of social disorganization theory have been more clearly articulated and extended by several authors (e.g., Kornhauser, 1978; Bursik and Grasmick, 1993; Sampson and Groves, 1989) and integrated with additional theoretical perspectives by others (e.g., Sampson and Wilson, 1995; Stark, 1987; Taylor, 1997).

Urban settings have been the dominant focus of both theoretical development and empirical research, not only for social disorganization theory in particular, but for the study of community influences on crime in general. For instance, many of the largest cities in the United States have been the subject of ecological studies of crime (e.g., Chicago, New York, Boston, Baltimore, San Diego). Shannon's (1988) research on Racine, Wisconsin (1990) population 84,000) is a lone example of research on a smaller city.

Though ecological and social disorganization theorists have not attended to communities, rural areas have been included in some studies of communities and crime. Many of these studies (Sampson, 1983, 1985; Sampson and Groves, 1989) were based on victimization surveys that used national samples rather than samples of limited geographic areas (e.g., neighborhoods within a city). The results of these studies are, indeed, supportive of social disorganization theory. Nevertheless, the studies either did not systematically examine the applicability of the theory within non-metropolitan areas (Sampson, 1985; Sampson and Groves, 1989) or limited their attention to a specific structural variable (Sampson, 1983). Sampson and Groves' (1989) influential study is set in Britain rather than the United States. We know of only three studies of variation in crime rates among rural communities. One of these uses a small sample of counties (13) from a limited region of Georgia (Arthur, 1991), another concerns the contrast of homicide rates with rates of other

social problems (Wilkinson, 1984b), and the third, though based on social disorganization theory, is so brief that it is difficult to evaluate its strengths and weaknesses (Petee and Kowalski, 1993). To date, there has been no systematic test of the relevance of social disorganization theory to non-metropolitan communities.

## EXTENDING SOCIAL DISORGANIZATION THEORY BEYOND THE METROPOLIS

Considering the origins of the concept of social disorganization, the lack of attention to non-urban communities is a glaring omission. Thomas and Znaniecki (1958 [1927]) originally developed this concept to explain the disruptive impact of migration and industrialization on rural communities in Poland, as well as to explain delinquency in Chicago. Like urban communities, rural communities and smaller towns will surely vary in their ability to realize values and solve problems, so the idea of social disorganization is certainly applicable there.

Current thinking about social disorganization is heavily influenced by Kornhauser's (1978) careful reformulation of Shaw and McKay's (1942) approach. Kornhauser argued that it was most productive to view community level social control processes as the essential mechanism by which social disorganization affects crime and delinquency. She rejected the elements of cultural conflict and strain in Shaw and McKay's writings as unnecessary and not logically consistent with the remainder of the theory. Her perspective portrays structural factors such as poverty and ethnic heterogeneity as leading to higher delinquency rates because they interfere with community members' ability to work together in socializing and supervising their children.

Since Kornhauser's writing, the dominant direction of theoretical development for social disorganization theory has been to treat systems of social relationships as the source of community level social control. Bursik and Grasmick (1993: 4) write that the fundamental assumption of this systemic approach is that the effectiveness of social control "is determined

by the extensiveness and density of the formal and informal networks within the neighborhood that bind the residents together as a social community." The authors who have developed this approach (e.g., Bursik and Grasmick, 1993; Sampson, 1987; Sampson and Groves, 1989) draw heavily on systemic community organization theory from urban sociology (Berry and Kasarda, 1977; Hunter, 1985).

Following Hunter (1985), Bursik and Grasmick (1993) distinguish three levels of these systems of relationships. The first is the private order of social control, which is based on intimate, informal, primary groups. The stronger the system of primary relationships in a community, the greater the capacity to control unacceptable behavior by such means as criticism, ridicule, and ostracism (Bursik and Grasmick, 1993: 16). The next level is the parochial system of control, which "represents the effects of the broader local interpersonal networks and the interlocking of local institutions . . . " (Bursik and Grasmick, 1993: 17). When a community has a broad and dense network of these relationships of acquaintance and mutual acceptance, then social control for any child extends beyond his or her family and their close friends to encompass a substantial portion of the community. This network increases the capacity for informal surveillance (because residents are easily distinguished from outsiders), for supervision (because acquaintances will be willing to intervene in unacceptable behavior), and for shared involvement in the socialization of children. The third system concerns the external relationships between this community and others. This "public" order "focuses on the ability of the community to secure public goods and services that are allocated by agencies located outside the neighborhood." (Bursik and Grasmick, 1993: 17)

Though much of this reasoning is borrowed from urban sociology, we argue that these systems of relationships are as relevant to crime and delinquency in small towns and rural communities as in urban neighborhoods. The logic by which primary, parochial, and public

spheres would affect social control has everything to do with general principles of social relations and nothing to do with urban versus rural settings. As we read the theoretical literature on social disorganization, the only aspect that is uniquely urban is the explanation of why social disorganization arises in some geographic locations rather than others, such as Burgess' (1925) notion of concentric rings of urban development.

Our view about the generality of these systemic processes of social control is supported by work on rural settings. For instance, rural sociologists have been quite concerned with the disruptive effects of rapid population growth that occasionally occurs in rural areas. Freudenberg has argued that the negative effects of this "boomtown" phenomenon center on crime and other problems of social control, rather than on alienation and mental health difficulties (Freudenberg, 1986; Freudenberg and Jones, 1991). Furthermore, he explained these problems of social control by the same logic as systemic social disorganization theory: Rapid growth greatly diminishes the density of personal acquaintanceship in the community, which in turn interferes with surveillance and socialization of the young (Freudenberg, 1986).

In another line of research, Wilkinson (1984b) used systemic ideas to account for the differential rates of crime and other social problems in rural versus urban settings. His thinking was based on Granovetter's (1973) notion of strong versus weak social ties, which corresponds to the distinction between private and parochial systems of relationships. Wilkinson reasoned that primary relationships will constitute a larger portion of the social network of rural residents than of urban residents, due to limited population size and density. He then argued that the predominance of strong (or primary) ties in rural areas would enhance social control and thereby reduce most types of crime. At the same time, the lack of weak (or parochial) ties would make rural residents more vulnerable to disruptions in their primary

networks because they lack alternative sources of social support. Thus, rural communities would have higher rates of suicide and intimate violence.

As a first step in testing the applicability of social disorganization theory outside of large urban areas, we present a county level analysis relating youth violence to the structural characteristics of communities specified by social disorganization theory. These structural correlates have long been the primary basis of support for the theory in analyses of urban areas (e.g., Bursik, 1988). Results supportive of the theory's applicability to non-metropolitan areas would call for launching research integrating individual and community levels of analysis, which is necessary for directly examining the systemic mediating processes discussed above (Bursik, 1988; Sampson, 1987). Studies of this type have been critical to the advance of research on crime in urban communities (Elliott, Wilson, Huizinga, Sampson, Elliott, and Rankin, 1996; Gottfredson, McNeil, and Gottfredson, 1991; Sampson and Groves, 1989; Sampson, et al., 1997; Simcha-Fagan and Schwartz, 1986). We focus on youth violence because social disorganization theory emphasized adult socialization and supervision of adolescents and, accordingly, juvenile delinquency (rather than adult crime) has been a special emphasis of both early and recent research in the social disorganization tradition.

# STRUCTURAL CORRELATES OF YOUTH VIOLENCE OUTSIDE THE METROPOLIS

Social disorganization theory specifies that several structural variables influence a community's capacity to develop and maintain a strong social organization by influencing the systems of relationships described above. To test the theory's applicability to nonmetropolitan settings, we examine the relationships of these structural variables to rates of offending, for it is these relationships that have long provided the core empirical support for the theory in urban settings.

Hypothesis 1: Rates of juvenile violence will be positively related to residential instability, or high turnover of the population in an area. When the population of an area is constantly changing, there is less opportunity for residents to develop widespread and strong personal ties to one another and to community organizations (e.g., Bursik, 1988). This has been a central theme of theory and research on social disorganization since its inception, and it is the core assertion of the systemic model of urban social organization (Kasarda & Janowitz, 1974; Sampson, 1988). Massive population change is also the essential independent variable underlying the "boomtown" research on rural settings (Freudenberg, 1986; Freudenberg and Jones, 1991).

Hypothesis 2: Rates of juvenile violence will be positively related to ethnic heterogeneity. An important feature of Shaw and McKay's (1942) conception is that ethnic diversity presents problems of social disorganization by interfering with communication among adults who would wish to control their children's behavior. Effective communication is less likely in the face of ethnic diversity because differences in customs and a lack of shared experience may breed fear and mistrust, even when groups share conventional values opposed to delinquency (e.g., Sampson and Groves, 1989). In Bursik and Grasmick's (1993) terms, social control is limited because divisions between primary groups constitute a weak system of parochial relationships. It is important to distinguish this theoretically driven hypothesis about heterogeneity from simple ethnic differences in offense rates, which have very different implications.

Hypothesis 3: Rates of juvenile violence will be positively related to <u>family</u> disruption. Sampson (1985, Sampson and Groves, 1989) has added family disruption (e.g., divorce or single parent households) to Shaw and McKay's list of structural indicators of social disorganization. He reasons that unshared parenting strains parents' resources of time, money,

and so forth, interfering with parents' abilities to supervise their children and communicate with other adults in the neighborhood. Furthermore, the fewer parents in a community relative to the number of children, the more limited the networks of adult supervision that are imposed on all the children.

We expect these first three hypotheses from urban community research to hold for rural communities as well. We see no reason that these factors would not affect the organization of rural communities in a manner similar to urban communities. For the next two factors, economic status and population density, it is not clear that this should be the case.

Hypothesis 4: Rates of juvenile violence will be positively related to low economic status. According to Park and Burgess' (1924; Burgess, 1925) theory of urban ecology, the continual growth of major urban areas leads to the decline of residential areas closest to the central business district. These then become the areas most readily available to the poor and to the variety of groups who newly migrate to the area. Thus, areas with the lowest average socio-economic status will also have greater residential instability and ethnic heterogeneity, which will in turn lead to weaker systems of social control and higher rates of crime and delinquency (Bursik and Grasmick, 1993: 39). There is broad agreement that there is a reliable bivariate relationship between rates of poverty and delinquency in urban settings (e.g., Warner and Pierce, 1993), and some research suggests that the relationship of poverty to delinquency may be accounted for by other structural factors (e.g., Sampson, 1985; Smith and Jarjoura, 1988), as is specified by social disorganization theory.

In this argument, dynamics that are specifically urban provide the link between poverty and population turnover. This logic is not directly applicable to non-metropolitan settings where population loss is at least as common as growth, where growth may not follow the urban spatial pattern, and where poor populations may be stable and ethnically homogeneous.

Indeed, if a relationship between poverty and youth violence emerges for a sample of small towns and rural communities, it would likely reflect some other process in which community economic status has a more direct impact on social disorganization. If this were the case, then it would appear that systems of social relationships suffer from the difficulties of everyday life that directly stem from a lack of economic resources, rather than from the indirect mechanisms specified in standard versions of social disorganization theory.

Hypothesis 5: Rates of juvenile violence will be positively related to population density. Population density is rather different from the other structural factors for two reasons. First, evidence of a relationship of population density to urban crime and delinquency is much less consistent (Figueroa-McDonough, 1991). Second, the significance of density becomes quite different for non-urban communities, where in the least dense areas one must travel several miles to have significant contact with non-family members. The original reasoning about the urban context was that high density created problems by producing anonymity that interferes with social controls. Instead, the least dense rural areas may face a problem of social isolation that can limit social support to monitor children and respond to problem behavior. On the other hand, Sampson (1983) suggested that density may be more important in terms of opportunities for offending than in terms of social disorganization. An integration of social disorganization and routine activities, along the lines suggested by Bursik and Grasmick (1993), might imply that the relative isolation of living in a sparsely populated area would reduce opportunities for offending in the form of distance from targets and from potential companions in crime (Cohen and Felson, 1979; Osgood, Wilson, Bachman, O'Malley, and Johnston, 1996). This possibility is supported by Laub's (1983b: 189) finding that victimization rates are lowest in communities with the smallest populations, but only for

populations of 25,000 or less. In larger communities, rates were essentially unrelated to population size.

Hypothesis 6: Rates of juvenile violence will be higher in communities that are closer to urban areas. With this hypothesis we go beyond the themes of Shaw and McKay's work to an issue that is specific to rural settings and to the linkages among communities. Heitgerd and Bursik (1987) have argued that it social disorganization theory has been unduly limited to the internal dynamics of communities, and they have shown that rates of delinquency are also a function of relationships between neighboring communities. Various rural and suburban communities have very different relationships with urban communities, and this is an important theme of research on rural settings. In their pioneering research, Thomas and Znaniecki (1958 [1927]) concluded that the primary source of social disorganization for peasant villages was the young villagers' contacts with urban communities. Heitgerd and Bursik (1987: 785) propose that there may be a diffusion of delinquency across communities. They note that their findings for urban neighborhoods suggest that "less delinquent groups of youths are being socialized into more sophisticated types of criminal behavior by youths in adjoining areas." Because average crime rates are higher in counties with larger populations, diffusion of this sort would produce higher rates of delinquency in those non-metropolitan counties that are adjacent to metropolitan counties.

#### **METHODS**

## SAMPLE

One of the principal weaknesses of community level research on delinquency is that most studies focus on variation among neighborhoods within a single metropolitan area. As Bursik has pointed out (1988), this yields a weak base for generalizing results, and there has been no way of resolving inconsistencies in findings that have arisen across studies of different

cities. In the same vein, a county level analysis would be more meaningful if it were based on more than a single state. Thus, our analysis includes four states with substantial non-metropolitan populations: Florida, Georgia, South Carolina, and Nebraska.<sup>2</sup>

The standard unit of analysis for research in the urban setting has been neighborhoods that are no more than a few miles across. This conception of community does not generalize very well to rural settings where population density is much lower. Because both arrest data (from the Uniform Crime Reports) and population characteristics (from Census Bureau population reports) are available at the county level, this is a convenient unit of analysis for the study of community influences on rural crime rates. This is also a common unit of analysis in rural research of all types because counties typically have strong internal economic and governmental structures. It should not be forgotten, however, that most counties include several distinct communities. The county level of analysis is necessitated by the availability of data, but it is not the ideal unit for testing social disorganization concepts.

Our analysis is limited to counties that are not included in metropolitan statistical areas (MSAs) by the Census Bureau. These are counties that neither have a city of 50,000 or more, nor have 50% of their population residing in a metropolitan area of 100,000 or more. Thus, residents of these counties live in smaller cities, towns, and open country rather than in moderate to large cities or their suburbs.

No doubt some non-metropolitan counties encompass two or more distinct communities that differ in their level of social disorganization, just as city neighborhoods defined by census boundaries may combine diverse settings. It is important to recognize that, though our research design treats a single value of each variable as characteristic of an entire county, there may be communities within a county that deviate from that average. Inaccuracy of this sort will decrease the variation in our explanatory variables, with the statistical

consequence of reduced power to detect relationships. Nevertheless, if there is a meaningful level of variation across counties, then strong relationships should be apparent, and there is no reason that a lack of precision would introduce systematic biases.<sup>3</sup> Indeed, Land, McCall and Cohen (1990) demonstrated that structural correlates of crime rates are generally robust across city, county and state levels of aggregation. Their results suggest that our county level analysis should provide a reasonable approximation to the relationships that would be found with more precisely defined communities.

Our analysis included 264 counties with total populations ranging from 560 to 98,000. Though these rural counties are much larger geographic units than the areas analyzed in community level research on crime in urban settings, they are of equal or smaller size in terms of population. The average total population of these rural counties is roughly 10,000, and that is considerably less than the widely studied 75 community areas of Chicago (e.g., Curry and Spergel, 1988), which have an average population of more than 37,000, and it is comparable to the more fine-grained analyses of 343 Chicago neighborhoods with an average population of a little over 8,000 by Sampson et al. (1997) and of 61 Boston neighborhoods with an average population of 9,249 by Warner and Pierce (1993). Thus, our sample compares favorably with studies of urban areas in terms of the number of aggregate units, the level of aggregation, and the breadth of settings included.

# MEASURES<sup>4</sup>

Delinquency. State criminal justice agencies routinely gather county level arrest data for inclusion in the Uniform Crime Reports (UCR, Federal Bureau of Investigation, 1997). These data are the obvious starting point for analyses of crime and delinquency in rural areas, and previous community level studies of rural crime have relied on this measure (Arthur, 1991; Pettee and Kowalski, 1993; Wilkinson, 1984a, 1984b). Criminologists have long been

concerned about potential biases in crime rates based on official records, especially arrests. A decade ago Bursik (1988) reviewed a variety of potential shortcomings of arrest records that might render worthless the entire body of social disorganization research. Fortunately, findings relating social disorganization to arrests have been replicated by more recent studies measuring offending through citizen calls for police assistance (Warner and Pierce, 1993), self-reports of victims (Sampson, 1985; Sampson and Groves, 1989), and self-reports of offenders (Elliott, et al., 1996; Gottfredson, et al., 1991; Simcha-Fagan and Schwartz, 1986).

Though this impressive degree of convergence across methods is encouraging, it does not guarantee that arrest records provide an appropriate index of non-metropolitan crime rates. There is a distinct possibility that arrest practices would be more informal in rural jurisdictions, where law enforcement officers are more likely to have personal ties to the families of the juveniles they apprehend. Another potential difficulty is that people arrested in a given county do not necessarily live there, which means that arrests may not be allocated to the jurisdiction of interest and we may not have an imprecise denominator for computing the arrest rate. In a rural county with substantial tourism, the per capita arrest rate might be considerably inflated by arrests of visitors. Conversely, the UCR juvenile arrest rate would be an underestimate of arrests for local youth if much of their misbehavior occurred during visits to other counties—which may be likely if entertainment and recreational facilities are more plentiful there. It should be remembered, however, that equivalent difficulties arise for research on urban settings, where arrests may be displaced to areas with entertainment districts, sports facilities, and so forth.

To date there have been no studies of the validity of arrest statistics in rural jurisdictions, and recent reviews of research on rural crime have not addressed this topic (Donnermeyer, 1994, Weisheit, et al., 1995). The best that can be said is that some support

for arrest statistics in rural areas is implicit in Laub's (1983a, 1983b) and Bachman's (1992) analyses of victimization data, which indicated that demographic correlates of crime rates (e.g., age, sex, race, time trends) are consistent between urban and rural areas and consistent with arrest data. Though research supports the validity of arrest data for assessing differences among communities in offense rates for urban communities, direct assessment of the validity of this measure for rural communities awaits future research.

Our measure of delinquency is the number of arrests of juveniles (ages 11 through 17) in each county, pooled over a 5-year period from 1989 through 1993. The primary dependent variables in our analyses were arrests for homicide, forcible rape, aggravated assault, robbery, weapons offenses, simple assault, and the Uniform Crime Reports (UCR) violence index, which is the sum for the first four offenses. Following the advice of authors such as Hindelang (1981) and Gove, Hughes, and Geerken (1985), the common practice in research on communities and crime is to limit analyses to a few offenses judged to be most reliably measured, such as homicide and robbery. Instead, we include a broad spectrum of those violent offenses for which recording is comparable across these four states, thereby capturing a relatively large range of offense seriousness. The potential advantage of our approach is that we have a rich pool of information for establishing the consistency of our findings.

Table 1 presents descriptive statistics for all of our measures, calculated separately for each state. Rates of arrest for serious violent offenses are considerably higher in the non-metropolitan counties of Florida and South Carolina than in those of Georgia or Nebraska.

Differences are less consistent for simple assaults. We suspect that some of these inconsistencies, such as the extremely low rate of simple assault in Florida, may reflect that police and citizens give less attention to minor offenses in areas with high rates of serious offenses (as noted by Smith, 1986 and Stark, 1987).

### Table 1 about here.

Explanatory Variables. Our measures of the explanatory variables associated with social disorganization theory were based primarily on 1990 census data (United States Department of Commerce, 1992). As is standard in research in this area, we defined residential instability as the proportion of households occupied by persons who had moved from another dwelling in the previous five years (e.g., Sampson, 1985; Warner and Pierce, 1993).

We measured ethnic heterogeneity in terms of the proportion of households occupied by white versus non-white persons. Following many researchers in this area (e.g., Sampson and Groves, 1989; Warner and Pierce, 1993), we calibrated ethnic heterogeneity with the index of diversity, calculated as  $1 - (\Sigma p_i^2)$ , where  $p_i$  is the proportion of households of a given ethnic group, which is squared and summed across the groups that are distinguished (here only white and non-white). This index reflects the probability that two randomly drawn individuals would differ in ethnicity (Blau, 1977). A county entirely comprised of white households or of non-white households would receive the minimum score of 0, while a county with equal numbers of white and non-white households would receive the maximum score of .5.

Family disruption was indexed by female-headed households, expressed as a proportion of all households with children. Previous studies have more often calibrated female headed households with children as a proportion of all households (e.g., Sampson, 1985; Warner and Pierce, 1993). We reasoned, however, that the burden of monitoring the behavior of children and teenagers falls disproportionately on adults in households with children (especially mothers), so that the proportion of mothers without marital partners would be most relevant to delinquency. Indeed, preliminary analysis indicated that an index based on

households with children was more strongly related to crime rates than was an index based on total households.

We defined poverty as the proportion of persons living below the poverty level. Some research indicates that there may be a threshold effect of low economic status rather than a continuous one (Figueroa-McDonough, 1991), with rates of true poverty more important than average incomes. In preliminary analyses, we investigated two indices of poverty: simple poverty, defined as the proportion of persons living below the poverty level, and extreme poverty, defined as the proportion of persons living below half of the poverty level. The simple poverty index proved to be more consistently related to juvenile arrest rates, so it is used in the analyses reported here. Our second measure of economic resources is the unemployment rate (coded as proportion of the workforce). We collected this information from State Data Centers, and we calculated a mean rate for the period under analysis.

Proximity to metropolitan counties was indicated by a dummy coded variable based on Beale Code designations (United States Government Accounting Office, 1989), with 1 being adjacent to a metropolitan statistical area and 0 being non-adjacent. Also included in the analysis were the number of youth 10 to 17 years of age, which is the population at risk for juvenile arrests. The geographic area of counties varies little within each state, so the population size measure is highly collinear with population density (r = .92). Therefore, we use population size as a proxy measure for population density in our models. Because states may differ in their statutes and in the organization, funding, and policies of their justice systems, it was important that we eliminate from our analysis all variation between states and assess only within-state relationships pooled across the states. We accomplished this by controlling for dummy variables representing states (with Florida serving as the omitted reference category). <sup>5</sup>

Because we control for differences between states in our analysis, our power to detect relationships is dependent on within-state variation in our measures. As can be seen in Table 1, there is substantial variation within each state for rates of arrest for all but the most rare offenses (i.e., homicide and rape in all four states and robbery in Nebraska). Similarly, the means and standard deviations of the explanatory variables reflect that there is meaningful variation within each state for rates of all of these phenomena except unemployment. Because unemployment rates were relatively constant within each state, we have limited statistical power to detect any impact of unemployment on delinquency.

### STATISTICAL MODEL

The outcome of interest for our analysis is the arrest rate, defined as the number of arrests in a county divided by the size of the population at risk for arrest. The standard approach to analyzing per capita rates such as these is to compute the rate for each aggregate unit and to use the computed rates (or a transformed version of them) as the dependent variable in ordinary least squares regression. This approach is inappropriate for our study because, for many of the aggregate units, the offense rate is low relative to the population size. As population size grows smaller, the crime rate becomes less precise and its distribution becomes increasingly skewed and discrete. We resolve these problems through a Poisson based regression model that is well suited to an outcome measures that is based on a count of events. Though Poisson based regression models have become prominent in the analysis of criminal careers (e.g., Land, McCall, and Nagin, 1996), they rarely have been applied to the aggregate analysis of crime or other social phenomena.

For a detailed discussion of these statistical problems and their resolution through Poisson based regression, see Osgood (1999), which is intended as a companion piece to the present study. Here we will just mention the essential features of our statistical model. The

standard form for a Poisson based regression model is that the outcome measure is a count of events, and its mean is expected to be the natural logarithm of a linear model (i.e., the sum of a set of explanatory variables each multiplied by a regression coefficient). Of course, our interest is in arrest rates relative to population size, rather than in numbers of offenses. To convert the model to this form, we add the natural logarithm of the size of the population at risk in each county to the linear model, giving that variable a fixed coefficient of one. This simple technique for standardizing the model is discussed in most presentations of Poisson based regression (e.g., Gardner, Mulvey, & Shaw, 1995; King, 1989; Liao, 1994; McCullagh & Nelder, 1989). A strict Poisson model assumes that the linear model explains all the meaningful variation in crimes rates among the sample of counties. To avoid this implausible assumption, we use the negative binomial variant of Poisson regression, which adds a term for residual variance in the underlying crime rates. We used the LIMDEP statistical package to conduct our analyses (Greene, 1995).

#### **RESULTS**

#### MODEL COMPARISONS

Before turning to the specific explanatory variables associated with social disorganization theory, we first compare models with differing levels of complexity in order to determine the necessity of including certain types of factors. We tested whether the size or density of the juvenile population had a substantive effect on juvenile violence rates by comparing models with and without the constraint that the coefficient for log population at risk equal one. A significant increase in the explanatory power of the model would indicate that per capita arrest rates vary with population size. The portion of Table 2 labeled "Linear Effect of Log Population" reports these significance tests. Both models in this comparison also controlled for the other six explanatory variables (residential instability, female headed

households, ethnic heterogeneity, poverty rate, unemployment, and adjacency to metropolitan area), to insure that effects of population size would not be attributable to those variables. These and all other models also control for differences between states with a set of dummy variables. The significance test is a likelihood ratio test, which is computed by taking twice the difference of the log likelihoods of the models being compared. One compares this value to the  $\chi^2$  distribution, with degrees of freedom equal to the number of parameters added to the model. These tests reveal that per capita arrest rates do, indeed, depend on population size for all offenses except homicide and rape.

#### Table 2 about here.

The strong dependence of per capita arrest rates on population size (or density) prompted us to explore whether the relationship of arrest rate to population size might be curvilinear. We allowed for a cubic relationship by adding squared and cubed terms for log population at risk. In order to reduce collinearity and improve the efficiency of the estimation, we transformed population size to deviations from the mean before raising it to higher powers. Likelihood ratio tests of the cubic versus linear relationship of arrest rates appear in the second portion of Table 2. These results were more variable across the specific offenses. The relationship of per capita arrest rate to population size was significantly non-linear for the violence index, aggravated assault, and simple assault, but not for homicide. For rape, the deviation from linearity was of borderline significance, as was the overall relationship of population size to offending ( $\chi^2 = 6.82$ , df = 3, p = .078).

The third set of model comparisons reported in Table 2 addresses whether the other six explanatory variables, considered in combination, account for significant variation in counties' per capita arrest rates. To insure that any differences detected were not attributable to

population size, this model comparison controlled for a cubic relationship of population size to offense rate.

As is shown in Table 2, these six explanatory variables account for significant variation in per capita arrest rates for the violent offense index and for all of the individual violent offenses except homicide. It is likely that our power to detect differences in homicide rates is limited by the low rate of homicides. Indeed, the homicide rate was low enough that juveniles committed no homicides in 69% of these counties over this five year period. Though arrests for rape were almost as rare as those for homicide, rape was significantly related to these variables.<sup>6</sup>

Our model comparisons make clear that per capita juvenile arrest rates are significantly related to at least some of the factors we have identified from social disorganization theory, and for population size (or density) the relationship is often nonlinear. We now turn to a more specific examination of these relationships.

### TEST OF TRADITIONAL SOCIAL DISORGANIZATION HYPOTHESES

Table 3 shows the primary results from our application of the traditional urban social disorganization model to rural counties. These negative binomial regression models include all of the explanatory variables (with the coefficients for population size estimated rather than fixed) and the dummy variables for states.<sup>7</sup> The model comparisons reported above determined the complexity of the controls for population size.

#### Table 3 about here.

As Land et al. (1990) have demonstrated, multivariate regression coefficients such as these may be unstable in aggregate analyses because collinearity tends to increase with higher and higher levels of aggregation. We took three steps to determine whether we face a serious problem of collinearity. First, we examined correlations among our explanatory variables,

which appear in the Appendix. The strongest correlation among these variables equals .63, and only one other correlation exceeds .5. This level of correlation is similar to that of neighborhood level studies of communities and crime with similar size population units (e.g., Warner and Pierce, 1993), and it does not appear problematic. Second, though standard means of computing collinearity diagnostics do not apply to our non-linear model, it is quite feasible to compute a version of one of the most useful diagnostics. The variance inflation factor (McClendon, 1994) corresponds to the proportionate increase in the variance of a regression coefficient due to collinearity, which is easily calculated by comparing standard errors from the full regression model to those from equivalent models that excludes other explanatory variables. In the multivariate models, variances of coefficients are roughly 60% greater for residential instability, 160% greater for female headed households and poverty, and largely unchanged for the remaining variables. This degree of variance inflation is acceptable in a sample of this size.

Our third step for addressing collinearity was to estimate bivariate relationships and compare them to the multivariate relationships. We estimated the bivariate relationship with a negative binomial model that included only the explanatory variable of interest, the dummy variables controlling for differences between states, and log population size with a fixed coefficient of one. These estimates also support the conclusion that collinearity does not present a problem in this analysis because the overall pattern of findings was quite consistent with the multivariate analysis. Strong and significant multivariate relationships were also strong and significant bivariate relationships. As would be expected, there was some tendency for the magnitude and significance of the bivariate relationships to exceed those of the multivariate relationships. Only for the poverty rate did the multivariate analysis produce

results that were discrepant from the bivariate analysis, and we discuss that finding in detail below. The bivariate estimates are available from the authors by request.

Residential instability. In accord with other studies of both urban (e.g., Sampson, 1985) and rural settings (Petee and Kowalski, 1993), we found residential instability to be associated with higher rates of rape, aggravated assault, weapons violations and simple assaults as well as the overall violent crime index. To gauge the strength of these relationships, consider that the coefficients reflect differences in log rates of offense, and a log difference of .69 corresponds to a doubling of offense rates (i.e.,  $e^{.69} = 2$ ). Thus, the coefficient of 2.86 for the violent crime index indicates that the arrest rate for violent offenses will double with a 24% increase in residential turnover in a five year span (i.e., 2.86 X .24 = .69).

Ethnic heterogeneity. Ethnic heterogeneity is significantly associated with higher rates of arrest for all of these violent offenses except homicide and simple assaults. The coefficient of 1.62 for the relationship of ethnic heterogeneity to the violence index implies that a 43% difference in the heterogeneity index (i.e., 85% of its range) would correspond to a doubling in the arrest rate.

The reader may wonder whether the results for ethnic heterogeneity truly reflect heterogeneity or if that variable is merely a proxy for the proportion of minority group members in the population. These variables are too highly correlated to address this directly by including both in the same model. To gain some perspective on the issue, we estimated models replacing ethnic heterogeneity with proportion non-white. Percent non-white was less strongly related to arrest rates, suggesting that heterogeneity is the more important variable.

Female headed households. Higher levels of family disruption, as indexed by the proportion of female headed households, were strongly and consistently associated with higher rates of arrest for violent offenses other than homicide. Given the bivariate coefficient of 5.31

for the violent crime index, an increase of 13% in female-headed households would produce a doubling of the offense rate, the strongest relationship in the model.

Poverty rate and unemployment. For this sample of non-metropolitan counties in four states, we do not find a meaningful relationship between delinquency rates and either of our indicators of economic status, poverty rate and unemployment. The results for unemployment are relatively uninformative because we lack statistical power. Most of these coefficients were positive, indicating an association of unemployment with higher arrest rates. Though the magnitude of some of these coefficients would reflect substantial relationships, their standard errors were extremely large, due to the limited variance in unemployment rates within each state.

We find no indication that poverty is associated with higher rates of delinquency.

Instead, the relationships are either very slight or negative, and for simple assault and rape the negative coefficients are statistically significant. The lack of positive relationship is not merely a matter of collinearity because none of the bivariate coefficients were significantly positive (or negative) either.

It is instructive to consider this finding in light of the correlation of poverty with the other explanatory variables (see Appendix). As is typical of urban research (e.g., Warner and Pierce, 1993), poverty in these non-metropolitan counties is positively associated with ethnic heterogeneity (r = .48, controlling for state) and with the rate of female headed households (r = .55). In contrast to urban areas, however, the correlation between poverty and residential instability is negative rather than positive (r = -.39). This contradicts the classic pattern of relationships from Park and Burgess' (1924; Burgess, 1925) theory of urban ecology, which was the basis for the predicting that poverty would lead to social disorganization. The association of poverty with ethnic heterogeneity would produce a positive correlation of

poverty with delinquency, but this would be canceled by the negative relationship of poverty with residential instability. There are also comparable off-setting relationships of poverty with the rate of female headed households and population size (r = -.40). This pattern of relationships is consistent with research conducted by Fitchen (1994), who found that the rural poor populations are not necessary highly mobile. She found that poorer residents do not make frequent moves in rural areas of the country when there is an abundance of low-cost housing and when residents have a support network of family and friends who are able to provide casual rent agreements and flexible payment schemes. It appears that poverty comes in a very different "structural package" in small towns and rural communities than in larger urban areas. Thus, though we find that a high rate of poverty does not increase the delinquency rate, that appears to be for reasons consistent with classic themes of social disorganization theory.

Proximity to metropolitan areas. Whether or not a rural county is adjacent to a metropolitan area appears to have no bearing on its rate of juvenile arrests for violent offenses. All of the coefficients for this explanatory variable are small, and none reach statistical significance. If there is a diffusion of delinquency across communities, such as Heitgerd and Bursik (1987) found for urban neighborhoods, it is not so simple as to be captured by this dichotomy of whether or not a county is adjacent to a metropolitan area.

Population size or density. As noted above, we used the size of the juvenile population as a proxy for population density because the two are essentially indistinguishable within each state. The relationship of population size to juvenile arrest rate is curvilinear for many of the offenses, so the coefficients of Table 3 are not especially helpful for judging either the magnitude or statistical significance of the contribution of population size. The model comparisons of Table 2 provide appropriate significance tests. Graphs are more helpful for

ascertaining the strength and form of the relationships, and Figure 1 illustrates the findings with graphs for four of the offenses.

## Figure 1 about here.

As can be seen in Figure 1, arrest rates for juvenile violence vary dramatically with differences in the sizes (or densities) of juvenile populations. For all violent offenses except homicide, variation in the size of counties' juvenile populations produces at least three-fold differences in juvenile arrest rates. Figure 1 shows that annual arrest rates for juvenile violence are uniformly lower in the rural counties with the smallest populations. For population sizes of 4,000 or less, per capita arrest rates rise with increases in juvenile population. Beyond this level, increasing population has little impact on arrest rates for violent offenses other than robbery. These findings are comparable to Laub's (1983b) report that victimization rates increase with population size, but only for total populations (rather than juvenile populations) up to about 25,000. For the violence index, rape, and aggravated assault in our data, arrest rates appear to decline somewhat in the upper range of juvenile population sizes, but it is unlikely that these decreases would be statistically significant.

### **CONCLUSIONS**

Social disorganization theory. Our findings indicate that the themes of social disorganization theory, developed in comparisons among urban neighborhoods, generalize well to rural communities. In these non-metropolitan counties, per capita rates of juvenile arrest for violent offenses are significantly and consistently associated with residential instability, family disruption, and ethnic heterogeneity. Due to a lack of variability, our sample was not well suited to studying structural correlates of unemployment.

From the strength and consistency of the findings, it appears that family disruption is an especially critical element of social disorganization in these non-metropolitan communities.

In terms of social disorganization theory, this suggests that adults actively engaged in parental roles are especially critical to the systems of relationships that bring formal and informal controls to bear on the behavior of children throughout the community.

Our results diverge from the standard findings for urban areas with regard to poverty and delinquency. Yet when we consider the structural correlates of poverty for this sample of non-metropolitan communities, we see that this finding is supportive of the core logic of social disorganization theory. Shaw and McKay (1942) saw the relationship of poverty to delinquency as mediated by residential instability and ethnic heterogeneity, and here they relied on Park and Burgess' (1924; Burgess, 1925) notions of population succession in the residential areas surrounding the core business districts of large urban centers. It should not be surprising that this urban population dynamic does not hold for our small towns and rural areas. Instead, a positive connection of poverty with ethnic heterogeneity is canceled by a negative connection with residential instability: Outside the metropolis, the populations of poorer communities may be more stable than average, not less. Thus, our findings support Shaw and McKay's (1942) contention that it is not poverty per se that produces social disorganization, but rather associations of poverty with other structural factors that weaken systems of social relationships in a community.

Population size. Our findings concerning the relationship of juvenile violence to the size and density of the juvenile population have interesting theoretical implications. From the premises of social disorganization theory, we hypothesized that high population density would interfere with social organization by creating anonymity and by increasing the difficulty of supervising children and adolescents. This reasoning implies that problems would accelerate at especially high densities. Yet the curvilinear relationship we did observe has the opposite

form: Population size makes little difference after reaching the modest density of about 4,000 juveniles in an entire county. Clearly another dynamic must be at work.

We believe that three opportunity explanations would be more plausible. The first, following Sampson (1983), is that opportunities for offending increase as population density increases. A small population reduces the chances that a potential robber would randomly encounter a likely victim or that two rivals would chance to meet in an unguarded setting conducive to an assault (Cohen and Felson, 1979). Furthermore, the company of peers provides support for engaging in delinquent behavior (Osgood, et al., 1996), and a very low population density will make it more difficult for peers to get together.

A second opportunity explanation focuses on opportunities to detect and report offenses. In a community with a very sparse population, there would be fewer likely witnesses who could observe offenses. In this case, population density would influence enforcement rather than violations of the law. It is less likely that differential enforcement would explain our findings, however, because Laub (1983b) found the same relationship of crime rates to population size in victim reports of offenses.

A third alternative is that the relationship of population size to crime rates is spuriously produced by adolescents in small communities venturing to larger communities to commit their crimes, which is where their offenses would be recorded. In this case the relationship would reflect the displacement of crime to an area with greater opportunities, rather than a true relationship of population size to crime. Though we cannot rule out this possibility, one piece of evidence weighs against it. We would expect this dynamic to be most evident for rural counties adjacent to metropolitan areas, which should offer the greatest opportunity for displacement. Adjacency was included in our models, and we found no such relationship.

Consistency across violent offenses. It is interesting to see the consistency of our findings across this full set of seven violent offenses. Many researchers limit their analyses to a few offenses presumed to be most reliably recorded, such as homicide and robbery. Indeed, there can be little doubt that law enforcement officers have less discretion about whether to make arrests for these offenses or that victims and bystanders are more likely to report them. Even so, the relationships of structural characteristics to the rate of simple assaults are nearly identical to those for the other violent offense categories such as rape and aggravated assault. Thus, instead of finding idiosyncratic and meaningless results for less serious offenses, we obtained additional confirmation for the overall pattern of our findings.

Future directions. We believe that we have been successful in our first step toward extending research on communities and crime beyond a narrow focus on urban centers to include the full range of communities in which Americans live today. Our study illustrates that themes from social disorganization theory have broader application to communities of all sizes. We also find that data from non-metropolitan communities can be especially useful for testing and expanding the theory because they present different patterns of structural variables. For instance, our findings related to poverty and crime suggest that non-metropolitan communities may provide the 'laboratory' in which the direct impact of poverty on community disorganization can be determined. Thus, social disorganization and related theories (e.g., Sampson and Wilson, 1995; Stark, 1987; Taylor, 1997) are appropriate starting points for developing either theories of crime specific to rural settings or theories of communities and crime that are general across settings. The critical task of developing such theories will require a firm grounding in the modern realities of settings ranging from small cities to isolated farming communities to suburbs ringing urban cores. These theories will need to take into account the varieties of lifestyles and of meanings of community across

communities of all types. For too long, theories of communities and crime have limited their attention to an image of small, dense urban neighborhoods that fully encompassed the lives of their inhabitants, and that image is out of synch with life in most communities in the United States today.

There are many possibilities for further research on crime in rural or non-metropolitan communities. A straightforward starting place would be to extend the present study in several ways. First, it would be worth expanding the sample of counties to insure that findings generalize beyond these four states, which were chosen for pragmatic rather than scientific reasons. With a larger and more representative sample of states, one could use random coefficient regression models such as hierarchical linear modeling to determine whether the correlates of county crime rates vary across states. The recent version of Bryk, Raudenbush, and Congdon's (1996) HLM program is capable of estimating a hierarchical version of a Poisson model, comparable to ours. Second, it is important to validate our findings for arrest rates by conducting comparable analyses of other measures of offending, such as self reports of offending and victimization surveys.

Third, it would be useful to expand the range of structural variables included in our analysis. The current analysis is limited by assessing ethnic heterogeneity only in terms of white versus non-white, and we have not examined some variables found to be important in other studies, such as structural density defined by the proportion of multiple-dwelling housing units (Sampson, 1983). Furthermore, it would also be interesting to explore additional elements of community heterogeneity that may be more pronounced in rural communities such as economic heterogeneity. The neighborhoods examined in urban areas are predominately homogenous in economic status, but many rural communities encompass a wide range of social classes and incomes. Also, though our initial exploration the impact of relationships

between communities proved unsuccessful, we believe that it would be worthwhile to study these relationships in a sophisticated manner. Rather than our simple dichotomous measure of adjacency to metropolitan areas, future research should incorporate measures of delinquency rates in adjacent areas and of the nature and strength of relationships between communities.

Finally, the success of this initial study also gives justification for investing in more sophisticated research on crime in non-metropolitan communities, research that reaches the full level of sophistication now found in the study of large urban centers. This will require going beyond census data in order to directly measure the social characteristics of communities that theories specify as affecting rates of crime and delinquency (Bursik, 1988; Sampson, 1987), especially the size and strength of networks of social relationships. Such research must also involve the integration of individual and community levels of analysis, which has contributed so much to the growing sophistication of research on urban communities (Elliott, et al., 1996; Gottfredson, et al., 1991; Sampson and Groves, 1989; Sampson et al., 1997; Simcha-Fagan and Schwartz, 1986).

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## NOTES

A related but distinct tradition of research uses entire cities rather than neighborhoods as the unit of analysis (e.g., Blau and Blau, 1982; Messner, 1982; Shihadeh and Steffensmeier, 1994). This tradition of research emphasizes the contribution of inequality to crime and entails explanatory variables reflecting comparisons among geographical subareas and subpopulations of cities (e.g., racial segregation or income inequality). Our work falls in the social disorganization tradition because the population sizes of our communities more closely match those of neighborhoods in social disorganization research and because social disorganization theory is more suited to our interests in adolescent offending, socialization, and social control.

<sup>2</sup> Many other states would be appropriate for this purpose as well. These four were chosen because the larger project through which this research was funded focused on the Southeastern U.S. Being aware of regional variations in both crime and the structural correlates specified in social disorganization theory, we chose to include a Midwestern plains state to assess the generalizability of our findings for a second region.

<sup>3</sup> Crane (1991) has argued that the relationship of community characteristics to outcomes such as delinquency will be non-linear, with problems especially prevalent under extreme conditions of deprivation. If he is correct, then combining diverse communities within aggregate units will attenuate the strength of our results. Even so, our results would be misleading only if the presence of extremely disorganized communities was unrelated to the average level of disorganization in the remainder of a county, which is implausible.

<sup>4</sup> Mike Overton of the Nebraska Commission on Law Enforcement and Criminal

Justice, Dave Pfiefer of the Center for Public Affairs Research at the University of Nebraska

at Omaha, Mary Sik of the Georgia Division of Demographic and Statistical Services, Mike

Macfarlane of the South Carolina Division of Research and Statistical Services, and Steven Kimble of the Florida State Data Center assisted us in obtaining these data.

To insure that single cases did not have undo influence on our results, we recoded some extreme values to values less deviant from the distribution as a whole. We set the maximum for residential stability to .6 (reduced from .76), for female headed households to .35 (reduced from .42), and for unemployment to .12 (reduced from .14). This recoding had no substantive impact on the results, and it increases our faith in their reliability.

<sup>6</sup> For the negative binomial model, power is highly dependent on the variation in the outcome variable. The model comparison of the fit of the Poisson model versus the negative binomial model is useful in this regard because it reflects the amount of meaningful variation among counties, beyond purely chance fluctuation generated by a Poisson process. The  $\chi^2$  value of this test (for the multivariate model) was 47.4 for homicide and 68.3 for rape. Though these values are statistically significant, they are trivial compared to the values of 500 to 6800 for the other offenses. In this light, it is impressive that arrest rates for rape are significantly related to the explanatory variables, and it is not surprising that rates for homicide are not.

<sup>7</sup> We also tested for potential interactions in which these substantive relations would vary across states or with population size. Only chance levels of interactive relationships emerged.

Table 1. Descriptive statistics for the sample of hon-metropolitan counties from four states.

|                           | Florida |           | Georgia |           | South Carolina |               | Nebraska      |            |
|---------------------------|---------|-----------|---------|-----------|----------------|---------------|---------------|------------|
|                           | Mean    | Std. Dev. | Mean    | Std. Dev. | Mean           | Std. Dev.     | Mean          | Std. Dev.  |
| Population at Risk        | 2941    | 2074      | 2287    | 1940      | 4926           | 2621          | 1091          | 1152       |
| Log Population at Risk    | 7.76    | .69       | 7.45    | .76       | 8.35           | .58           | 6.51          | 1.05       |
| Number of Counties        | 31      |           | 116     | ., 0      | 30             | .50           | 87            | 1.05       |
| Explanatory Variables     |         |           |         |           |                |               |               |            |
| Residential Instability   | .47     | .05       | .41     | .06       | .35            | .06           | .36           | .06        |
| Ethnic Heterogeneity      | .28     | .10       | .37     | .15       | .45            | .06           | .03           | .04        |
| Female Headed Households  | .18     | .04       | .22     | .07       | .24            | .04           | .09           | .04        |
| Poverty Rate              | .16     | .04       | .19     | .05       | .19            | .06           | .12           |            |
| Unemployment              | .08     | .02       | .07     | .01       | .08            | .00           | .03           | .04        |
| Adjacent to Metro. Area   | .74     | .44       | .53     | .50       | .80            | .41           | .03           | .01<br>.35 |
| Annual Arrest Rates per 1 | 00,000  |           |         |           |                |               |               |            |
| UCR Violent Crime Index   | 360.0   | 350.1     | 127.1   | 114.6     | 246.4          | 144.5         | 27.6          | 44.7       |
| Homicide                  | 12.2    | 16.8      | 4.8     | 9.9       | 10.7           | 12.2          | 1.0           | 4.1        |
| Rape                      | 19.5    | 24.7      | 8.2     | 12.3      | 25.7           | 20.0          | 2.8           |            |
| Robbery                   | 78.5    | 99.6      | 23.4    | 36.0      | 42.3           | 31.6          |               | 8.3        |
| Aggravated Assault        | 249.9   | 237.6     | 89.5    | 83.4      | 167.7          |               | 2.9           | 9.0        |
| Weapons                   | 45.2    | 52.6      | 36.9    | 49.6      | 88.8           | 106.2         | 20.9          | 36.1       |
| Simple Assault            | 169.9   | 200.1     | 159.7   | 163.8     | 343.9          | 47.9<br>342.0 | 22.9<br>182.4 | 46.5       |
| =                         |         | —         |         | 105.0     | J-7J.J         | J72.U         | 102.4         | 318.5      |

Table 2. Model comparisons for significance tests of the relationship of arrest rates to size of population at risk and to other explanatory variables.

|   | Violent<br><u>Crime Inde</u> | Homicide<br>x | Rape   | Robbery | Aggr.<br>Assault | Weapons | Simple<br>Assault |  |  |
|---|------------------------------|---------------|--------|---------|------------------|---------|-------------------|--|--|
| Linear Effect of Log Population: df = 1           |                              |               |        |         |                  |         |                   |  |  |
| $\chi^2$  | 18.10                        | 1.45          | .76    | 18.21   | 8.85             | 8.24    | 20.01             |  |  |
| p   | .000                         | .228          | .382   | .000    | .003             | .004    | .000              |  |  |
| Cubic Vs. Linear Effect of Log Population: df = 2 |                              |               |        |         |                  |         |                   |  |  |
| $\chi^2$  | 11.02                        | 2.57          | 5.92   | 3.05    | 10.10            | 3.12    | 10.28             |  |  |
| p   | .004                         | .277          | .052   | .218    | .006             | .210    | .006              |  |  |
| Additional Explanatory Variables: df = 6          |                              |               |        |         |                  |         |                   |  |  |
| $\chi^2$  | 43.76                        | 9.07          | 28.47  | 27.48   | 40.57            | 22.10   | 39.34             |  |  |
| p   | .000                         | .169          | .000   | .000    | .000             | .001    | .000              |  |  |
| -2 Log Likelihood for Overall Models              |                              |               |        |         |                  |         |                   |  |  |
| Base Model  | 1658.64                      | 486.80        | 674.76 | 950.88  | 1508.64          | 1206.12 | 1937.47           |  |  |
| Full Model  | 1563.96                      | 474.66        | 630.53 | 898.43  | 1426.20          | 1156.99 | 1832.86           |  |  |

Table 3. Multivariate relationships of explanatory variables to arrest rate from negative binomial regressions.

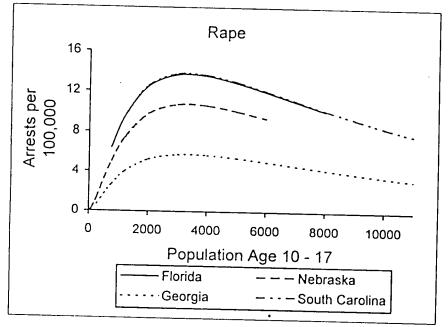
| Explanatory Variable             | Violent<br>Crime Inde | Homicide | Rape   | Robbery | Aggr.  | Weapons | Simple<br>Assault                       |  |
|----------------------------------|-----------------------|----------|--------|---------|--------|---------|---|--|
| Residential Instability  Assault |                       |          |        |         |        |         |   |  |
| ь                                | 2.858                 | .336     | 3.733  | .162    | 3.647  | 1.854   | 2 266                                   |  |
| s.e.                             | 1.147                 | 3.030    | 1.913  | 2.026   | 1.310  | 1.834   | 3.366<br>1.313                          |  |
| p                                | .013                  | .912     | .051   | .936    | .005   | .339    | .010                                    |  |
| Ethnic Heterog                   | eneity                |          |        | .,,,,,  | .005   | .557    | .010                                    |  |
| ь                                | 1.622                 | 2.387    | 1.128  | 2.861   | 1.089  | 2.087   | 1.922                                   |  |
| s.e.                             | .634                  | 2.114    | 1.309  | 1.156   | .633   | 1.040   | .877                                    |  |
| р                                | .011                  | .259     | .389   | .013    | .085   | .045    | .028                                    |  |
| Female Headed                    | Household             | is       |        |         |        |         | .020                                    |  |
| b                                | 5.306                 | -3.384   | 9.804  | 3.739   | 6.356  | 5.434   | 6.290                                   |  |
| s.e.                             | 1.542                 | 4.172    | 2.684  | 2.937   | 1.592  | 2.596   | 1.837                                   |  |
| p                                | .001                  | .417     | .000   | .203    | .000   | .036    | .001                                    |  |
| Poverty Rate                     |                       |          |        |         |        |         |   |  |
| ь                                | -1.967                | 6.081    | -6.540 | .021    | -2.916 | -3.887  | -4.862                                  |  |
| s.e.                             | 1.931                 | 4.668    | 3.260  | 3.381   | 2.058  | 3.379   | 2.149                                   |  |
| p                                | .309                  | .193     | .045   | .995    | .157   | .250    | .024                                    |  |
| Unemployment                     |                       |          |        |         |        |         | ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,, |  |
| ь                                | 1.386                 | -1.744   | 4.644  | .432    | .736   | 2.936   | .314                                    |  |
| s.e.                             | 4.118                 | 8.808    | 6.556  | 6.568   | 4.253  | 6.867   | 4.586                                   |  |
| р                                | .737                  | .843     | .479   | .948    | .863   | .669    | .945                                    |  |
| Adjacent to Metropolitan Area    |                       |          |        |         |        |         |   |  |
| ь                                | 138                   | .370     | 182    | 458     | 035    | 313     | 078                                     |  |
| s.e.                             | .133                  | .307     | .199   | .215    | .137   | .201    | .150                                    |  |
| р                                | .296                  | .227     | .361   | .034    | .800   | .119    | .601                                    |  |
| Population at Ri                 | sk                    |          |        |         |        |         |   |  |
| Log .                            |                       |          |        |         |        |         |   |  |
| ь                                | 1.673                 | 1.250    | 1.636  | 1.718   | 1.563  | 1.388   | 1.709                                   |  |
| s.e.                             | .151                  | .248     | .346   | .188    | .150   | .163    | .161                                    |  |
| p <sup>1</sup>                   | .000                  | .156     | .033   | .000    | .000   | .008    | .000                                    |  |
| Log Squared                      | 0.5                   |          |        |         |        |         |   |  |
| Ь                                | 217                   |          | 315    |         | 243    |         | 187                                     |  |
| s.e.                             | .099                  |          | .565   |         | .162   |         | .066                                    |  |
| p<br>oo Cubod                    | .029                  |          | .577   |         | .134   |         | .005                                    |  |
| Log Cubed                        |                       |          |        |         |        |         |   |  |
| b .                              | 030                   |          | 022    |         | 014    |         | 073                                     |  |
| s.e.                             | .075                  |          | .246   |         | .098   |         | .061                                    |  |
| р                                | .683                  |          | .928   |         | .883   |         | .230                                    |  |

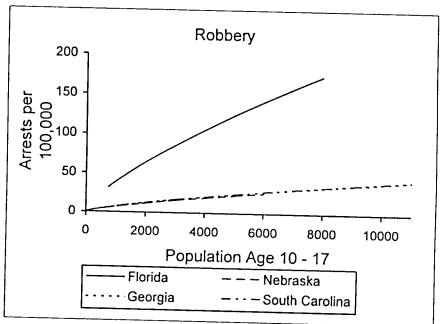
Table 3. (Continued)

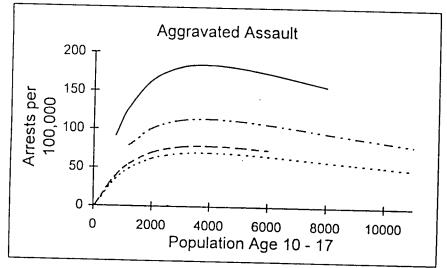
| Explana<br><u>Variable</u> | •    | Violent<br>Crime Inde |         | Rape    | Robbery | Aggr.<br>Assault | Weapons | Simple<br>Assault |
|----------------------------|------|-----------------------|---------|---------|---------|------------------|---------|-------------------|
| Constant                   |      |                       |         |         |         |                  |         |                   |
|                            | b    | -14.323               | -12.727 | -17.388 | -15.243 | -13.942          | -13.227 | -15.381           |
|                            | s.e. | 1.349                 | 2.520   | 3.319   | 1.722   | 1.393            | 1.510   | 1.633             |
|                            | p    | .000                  | .000    | .000    | .000    | .000             | .000    | .000              |
| $\alpha^2$                 |      | .444                  | .803    | .444    | .852    | .459             | .887    | .726              |

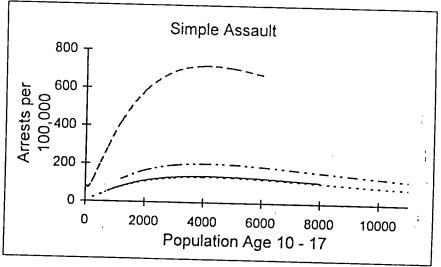
<sup>&</sup>lt;sup>1</sup>Significance test for difference of b from 1 rather than difference of b from 0.  $^{2}\alpha$  reflects unexplained variance residual variance beyond that expected from a simple Poisson process.

Figure 1. Relationship of population size to arrest rates for four violent offenses, controlling for other explanatory variables.









Appendix. Partial correlations among explanatory variables, controlling for differences between states.

| <u> </u>                 | Residential<br>Instability | Ethnic<br>Heterogeneity | Female Headed  Households | Poverty<br>Rate | Unemployment | Adjacent to<br>Metro. Area | Log Populationat Risk |
|--------------------------|----------------------------|-------------------------|---------------------------|-----------------|--------------|----------------------------|-----------------------|
| Residential Instability  | 1.000                      |                         |                           |                 |              |                            |                       |
| Ethnic Heterogeneity     | 250                        | 1.000                   |                           |                 |              |                            |                       |
| Female Headed Households | 145                        | .627                    | 1.000                     |                 |              |                            |                       |
| Poverty Rate             | 391                        | .479                    | .547                      | 1.000           |              |                            |                       |
| Unemployment             | 183                        | .158                    | .318                      | .331            | 1.000        |                            |                       |
| Adjacent to Metro. Area  | 008ª .                     | .117ª                   | .111ª                     | 170             | .101ª        | 1.000                      |                       |
| Log Population at Risk   | .382                       | 132                     | .077ª                     | 403             | .022ª        | .197                       | 1.000                 |

<sup>&</sup>lt;sup>a</sup> p > .05, all other correlations significant at p < .05.