

ASSESSING THE EFFECTS OF SOCIAL DISORGANIZATION
ON CRIME IN TEXAS BORDER COUNTIES:
A TIME-SERIES CROSS-SECTIONAL ANALYSIS FROM 1990 TO 2007

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ABSTRACT

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Guided by social disorganization theory, this study examines the relationship between structural factors and juvenile property crime in the 43 counties that form the Texas border region over an 18 year period. Measures are included for per capita income, unemployment, ethnic heterogeneity, residential instability, and urbanization, and fixed-effects panel regression is employed for the analysis. The results indicate that the structural factors associated with social disorganization theory are predictive of juvenile property crime within the region as a whole, and, while the other measures function

similarly in both rural and urban environments, the effect of per capita income on delinquency is significantly larger in urban environments.

Chapter One: Introduction

Social disorganization scholars have consistently shown that structural factors influence crime rates. While extant research has supported the influence of social disorganization in urban environments, much less is known regarding the influence of rural social disorganization on crime. Less is known because most social disorganization studies have been conducted in predominately racially Black Northeastern and Midwestern cities (Short, 1969; Small & Newman, 2001; Cancino, 2003). Consequently, there is limited information as to how social disorganization operates across rural Southwestern settings characterized by large Latino populations. Repeatedly testing social disorganization theory in the Northeast and Midwest represents a shortcoming in the social disorganization literature because theories are gauged by their ability to generalize across time, space, and setting. At this point, it is unclear how well social disorganization theory generalizes to ecologically distinct settings such as the Southwestern United States along the Texas-Mexico border. Additionally, there are other important reasons to adjudicate whether social disorganization operates similarly or differently among Latino populations in the Southwest.

First, it is unclear whether structural factors, such as those associated with social disorganization, affect crime equally across racial/ethnic groups (Martinez, 2002). Second, in both urban and rural areas, Latinos are a growing population characterized by high fertility and high immigration rates (Cancino, Martinez & Stowell, 2009). Third, while Latinos are more similar to Blacks than Whites regarding economic factors,

educational attainment, and access to opportunity, Latinos tend to do better on a number of negative social outcomes than Blacks (Palloni & Morenoff, 2001). Fourth, Latino communities may be impacted by the prevalence of recent immigrants in ways that Black communities are not (Martinez, 2002). Finally, Latino and Black communities may differ in their social networks' ability to exert social control (Moore & Pinderhughes, 1993).

Using seven independent data sources (Bureau of Economic Analysis, Bureau of Labor Statistics, Census Bureau, Texas State Demographer, Internal Revenue Service, Department of Agriculture Economic Research Service, and Uniform Crime Reports), the present study aims to evaluate the influence of social disorganization on juvenile property crime rates across urban and rural counties situated along the Southwest Texas-Mexico border. Employing a panel regression time-series cross-section analytical strategy, the research goal is to empirically determine whether county social disorganization structural conditions (poverty, unemployment, ethnic heterogeneity, and residential instability) impact juvenile property crime rates over an 18 year period. While previous social disorganization research has utilized cross-sectional techniques, the need to test the theory using longitudinal analysis has been clearly articulated (Bursik, 1988). To date, few scholars have endorsed studying the effects of social disorganization using a longitudinal approach (Bursik & Webb, 1982; Chamlin, 1989; Morenoff & Sampson, 1997). Moreover, no longitudinal studies of rural social disorganization and crime exist. The current study contributes to the literature by utilizing panel analysis, a pooled time-series technique described as possibly the strongest method for analyzing aggregate data (Marvel & Moody, 2008). In doing so, the study aims to answer two research questions. First, do the structural factors associated with social disorganization theory predict

juvenile property crime along the Texas-Mexico border? Second, are the relationships between structural factors (e.g., economic disadvantage, ethnic heterogeneity, residential instability) and crime different between urban and rural areas within the region?

Chapter Two: Literature Review

Social Disorganization Theory and Early Influences

Working within the Chicago School of Social Ecology, Clifford Shaw and Henry McKay (1942) studied juvenile delinquents across Chicago neighborhoods. In doing so, their research led to what is arguably one of the most important theoretical frameworks in the study of crime. Their theory, originally presented in *Juvenile Delinquency and Urban Areas* (1942), provided an ecological explanation for crime that remains influential within criminal justice and criminology (Short, 1969; Bursik, 1984; Sampson & Groves, 1989; South & Messner, 2000). Social disorganization posits that variation in the neighborhood factors of poverty, residential instability, and ethnic heterogeneity disrupts the mechanisms of social organization (Shaw & McKay, 1942). This disruption limits informal social control and undermines the ability of community members to achieve shared values and jointly solve problems, which, when present, minimizes crime and delinquency (Shaw & McKay, 1969; Kornhuaser, 1978; Bursik, 1988; Sampson & Groves, 1989). Although Shaw and McKay are given credit for social disorganization theory, much of their work was influenced by previous Chicago School researchers.

For example, Thomas and Znaniecki (1918) studied migration of Polish peasants in Poland and Chicago. Using qualitative ethnographic techniques, the researchers isolated cultural values of the migrant Polish and analyzed the effects of migration on homogenous communities. This led Thomas and Znaniecki to develop theories about the

effects of traditional community dissolution, social disintegration, and community solidarity on social organization. Although Thomas and Znaniecki were only indirectly interested in delinquency, Shaw and McKay would later utilize their broader conception of social disorganization in the development of a theory of crime.

Another team of researchers, Park and Burgess (1925), studied the relationship between city growth and social/physical decay in urban Chicago. Their methodology involved a concentric zone mapping technique which separated Chicago into zones based upon concentric circles drawn at different distances from the city's central business district. Park and Burgess defined the zones as the central business district (zone 1), transitional (zone 2), working class (zone 3), residential (zone 4), and commuter (zone 5). They noted that the transitional zone suffered from deteriorated housing, factories, and abandoned buildings and that neighborhood conditions improved as distance from the central business district increased. As a result, Park and Burgess hypothesized that social problems would be highest in the transitional zone due to its slum-like nature. Their research confirmed their hypothesis and showed that the transitional zone did demonstrate a higher density of social problems than the city's outer zones (Park & Burgess, 1925).

Building on prior social ecology scholarship, Shaw and McKay (1942) analyzed the social characteristics of Chicago neighborhoods and compared these characteristics with police and court records for juveniles. They found that rates of juvenile delinquency in Chicago were highest in transitional neighborhoods with high concentrations of non-native born and poor residents. The structural factors associated with these neighborhoods were low economic status, residential instability, and ethnic heterogeneity

(Shaw & McKay, 1942). The relationship between these factors and juvenile delinquency led Shaw and McKay to dismiss individualistic explanations in favor of ecologically-based explanations of crime. They claimed that low economic status, residential instability, and ethnic heterogeneity affected the social organization of communities, and that communities with less social organization would suffer from higher levels of crime (Shaw & McKay, 1969).

The first social disorganization structural factor Shaw and McKay identified was low economic status. They theorized that communities without sufficient resources lack the capacity to develop social organizations thereby limiting citizens' interactions with one another through meaningful social institutions. Without sufficient interaction, communities fail to develop awareness and ability to intervene on behalf of common goals, such as crime prevention. The second factor associated with social disorganization was residential instability. Here, they posited that a continuous stream of residents moving into and out of a community would undermine the development of social relationships among community members, again limiting interaction aimed at realizing effective mechanisms of informal social control. The final factor they considered was ethnic heterogeneity. Shaw and McKay theorized that different racial and ethnic groups bring diverse values and beliefs into a community, and that variation between the cultural values across groups disrupts the social equilibrium. All three factors lead to social disorganization which, in turn, limits the ability of a community to exert informal social control thereby fostering crime (Shaw & McKay, 1969).

In conducting their analysis, Shaw and McKay relied on a concentric zone model similar to the earlier work of Park and Burgess (1925). However, Shaw and McKay's

analysis added a substantial theoretical component by isolating the ecological factors present in the transitional zone and associating them with delinquency. Following Thomas and Znaniecki (1918), Shaw and McKay argued that these factors worked in conjunction with one another to disrupt community cohesion. Their reasoning was based on assumptions that communities characterized: 1) by poverty are composed of residents that lack a financial stake in the neighborhood, 2) by a constant influx and exodus of residents lack the stability required for residents to socially engage, and 3) by diverse racial/ethnic composition struggle with conflicting cultural differences making social organization difficult to achieve. Their findings supported their theory and showed that poor, transient, and ethnically diverse neighborhoods tended to have higher rates of crime (Shaw & McKay, 1942). While more contemporary research has refined the concepts associated with social disorganization theory, much of the classical theoretical framework remains intact.

Contemporary Social Disorganization Research

With improved data collection procedures and sophisticated analysis since the Chicago School, the social disorganization perspective has experienced some conceptual and measurement revisions. However, despite such revisions, numerous studies consistently show that poverty, ethnic heterogeneity, and residential instability adversely influence crime (Sampson & Groves, 1989; Chamlin, 1989; Warner & Pierce, 1993; Warner & Roundtree, 1997; Bellair, 1997; Kubrin, 2000; Osgood & Chambers, 2000; Barnett & Mencken, 2002; Cancino, 2003; Jobes, Barclay, Weinand, & Donnermeyer, 2004). Nevertheless, the theory has continued to evolve. Some scholars have worked to refine social disorganization measures (i.e., disadvantage in lieu of poverty or more

sophisticated measures of ethnic heterogeneity), while others significantly contributed to the theory by isolating the mechanisms affecting social disorganization within a community (e.g., collective efficacy, see Sampson, 1989). For example, Shaw and McKay's original research included poverty as a singular measure; however, more contemporary social disorganization scholars have created index/composite measures that also reflect poverty. In one such re-conceptualization, Wilson (1987) includes joblessness, out-of-wedlock births, single-mother families, lack of educational attainment, and welfare dependency as other aspects of poverty, or what he considers disadvantage.

Similarly, Sampson and Groves (1989) revised social disorganization by including family disruption as a measure of disadvantage. Their research showed that family disruption was related to crime. Using Sampson and Groves' (1989) data, Vesey and Messner (1999) found that family disruption remained related to crime even when using a covariance structure model which provided a more detailed decomposition of the individual relationships. Smith and Jarjoura (1988) also revealed a relationship between violent crime and single-parent households. Osgood and Chambers (2000) discovered that female-headed households were related to juvenile violent crime, and Shihadeh and Steffensmeier (1994) showed that welfare dependency was related to homicide. More recently, Jacob (2006) showed that educational attainment was negatively related to both property and violent crime.

Generally, this body of research shows substantial support for both the classical framework and the modern adaptations of social disorganization theory. Repeated testing, across a variety of environments and time periods, has added to social disorganization's

generalizeability, especially in urban environments. However, due to limited testing outside large urban centers, questions concerning the applicability of the theory in less densely populated regions have persisted. Few studies have considered social disorganization in settings outside the urbanized Midwest and Northeast.

Extending Social Disorganization to Rural Areas

Since its inception, social disorganization theory has traditionally been evaluated in large urban centers. Although Shaw and McKay conducted a majority of their social disorganization research within the city of Chicago, they did examine some areas outside the city. They conducted limited analysis of social disorganization in suburbs and satellite towns, but they did not specifically examine the theory in rural environments. In fact, Shaw and McKay (1969) argued that the capacity for social control may be much lower in urban communities when compared to rural communities. As a result, many contemporary studies incorporate urbanization as an exogenous aspect of social disorganization theory. This inclusion is supported, in part, on research conducted by Fischer (1982) who showed that urbanization was related to weaker local networks, including friendship and kinship, and that urbanization tended to limit social participation in local community affairs. Sampson and Groves (1989) tested the hypothesis that urbanization has an effect on social disorganization. Their research showed that urbanization had a limiting effect on friendships and a positive relationship with juvenile involvement in unsupervised peer groups. These findings have been supported by several additional studies including Veysey and Messner's (1999) re-analysis of Sampson and Grove's (1989) study, which again demonstrated the relationship between urbanization and social disorganization. Additional studies found similar support using proxy

measures for urbanization such as town or city size and population density (Tittle, 1989; Osgood & Chambers, 2000; Jacob, 2006).

Despite these findings, other research has suggested that there is substantial similarity between urban and rural crime. The similarities include patterns of offending and demographic factors such as age, sex, and race (Laub, 1983; Bachman, 1992). These findings support the contention that criminological theories based upon principles of community organization should apply to rural as well as urban areas (Laub, 1983; Osgood & Chambers, 2000). As such, theories developed to explain urban crime warrant testing in rural environments. A limited number of studies have attempted just that by extending social disorganization theory to rural environments.

In one particular study, Arthur (1991) tested the effects of socio-economic disadvantage and ethnicity on both violent and property crime in rural Georgia. The study used three measures of disadvantage including unemployment, percent of population living at or below the poverty line, and percent of families receiving government aid. Ethnicity was measured as percent Black. Data were analyzed for 1975, 1980, and 1985, and the study found that disadvantage and ethnicity were significant and positively associated with violent and property crime. The study, however, had several limitations. The study used counties as the unit of analysis, but had a limited sample size of 13. As a result, the generalizability of the findings is questionable. Furthermore, percent Black fails to directly measure ethnic heterogeneity as suggested by social disorganization theory.

Although directed at testing the relationship between poverty, ascriptive inequality, and nonlethal violence, research conducted by Wilkinson (1984) tested rural

social disorganization in the northeastern United States. Wilkinson operationalized ascriptive inequality by using percent Black as a proxy for his construct. As a result, the findings represent a test of social disorganization similar to the approach adopted by Arthur (1991). Wilkinson found that both poverty and percent Black were related to nonlethal violence. While the study used a larger sample of 278 counties, percent Black failed to capture ethnic heterogeneity as conceptualized by Shaw and McKay (1942).

Petee and Kowalski (1993) conducted a more traditional test of social disorganization in a rural environment. Using 630 rural counties from 1979 to 1986, Petee and Kowalski examined the relationship between rural violent crime and disadvantage, residential instability, and ethnic heterogeneity. Disadvantage was measured using percent of the population living with an annual income of less than \$7,500. Residential instability was measured using the percent of households occupied by persons who had moved within the last five years. Ethnic heterogeneity was measured using the ethnic diversity index (Greenberg, 1956), a sophisticated measure of heterogeneity equivalent to the ethnic heterogeneity index commonly used in more contemporary social disorganization research. The authors found that residential instability and ethnic heterogeneity were positively related to rural violent crime. They did not, however, find a significant effect for poverty.

While Petee and Kowalski's more sophisticated measurement using the ethnic diversity index helped to overcome some of the limitations when using percent Black to measure ethnic heterogeneity, other shortcomings were present in the study. Of primary concern was the nature of the data. The dependent variable (violent crime rate) was taken from the Uniform Crime Reports for each year between 1979 and 1986. However, the

independent variables, including poverty, residential instability, and ethnicity were derived exclusively from the 1980 U.S. Census data. This raises a potential methodological question as it fails to measure any ecological change within the counties over the eight-year period.

Fitchen (1994) conducted a study of rural residential instability that calls into question the applicability of common measures of residential instability when assessing rural social disorganization. His qualitative research indicates that the typical standard of measuring the percent of households occupied by persons who had moved within the last five years might not be appropriate for rural communities. He found that the rural poor have high residential instability, but a limited ability to move outside the communities where they reside. As such, they tend to migrate within the community rather than into and out of communities. The high prevalence of this micro-migration might affect the validity of the residential instability measurements based upon length of household occupation as the movers remain part of their community.

More recently, Osgood and Chambers (2000) studied social disorganization in rural environments. Their research examined the influence of residential instability, ethnic heterogeneity, family disruption, poverty, unemployment, proximity to metropolitan counties, and population density on rural youth violence across 264 rural counties. Osgood and Chambers found that residential instability, ethnic heterogeneity, and family disruption were associated with higher levels of violent crime excluding homicide. Poverty, unemployment, and proximity to metropolitan counties were not associated with higher levels of violent crime. Population density was related to higher

rates of offending, but the distribution of the data made it difficult to interpret the significance of the findings related to population density.

Barnett and Mencken (2002) performed an analysis similar to Osgood and Chambers using all non-metropolitan counties in the 48 contiguous United States. Relying on violent and property crime rates, their research showed that non-metropolitan counties tended to exhibit higher levels of resource disadvantage (poverty, income inequality, unemployment, and percent of female-headed households) and higher levels of social disorganization. While these factors were related to both types of crimes in rural environments, they were particularly important in counties that were experiencing population loss.

Cancino (2003) tested social disorganization in rural Michigan. The study focused on the relationship between social disorganization and perceived burglary. The use of perception of crime as a measure of crime was unique among rural social disorganization research. Using hierarchical linear modeling, the study considered socio-economic status, minority status, and residential instability at an individual level. Economic disadvantage was measured at the residential unit level. The results indicated that economic disadvantage and social cohesion operating at the residential unit level were significantly and positively related to perceived crime.

Jobes et al. (2004) extended social disorganization research to rural Australia. Using Australian census data and official crime statistics, the study focused on transition in rural New South Wales and used assault, breaking and entering, car theft, and malicious damage as measures of crime. The analysis found relationships between residential instability, proportion of indigenous population, and crime consistent with

social disorganization theory. Using a cluster analysis, the researchers isolated six distinct communities within the area. They were large urban centers, coastal communities, satellite communities, medium stable communities (those showing no substantial population change), medium unstable communities (those showing significant population changes), and small inland communities. They noted that the medium unstable communities exhibited the highest levels of the three types of property crime, again supporting social disorganization theory.

Existing research shows that community social disorganization is related to crime and delinquency with the majority of studies showing support for the relationship between the major theoretical predictors (economic disadvantage, ethnic heterogeneity, and residential instability) and crime. Additional research has supported the contention that social disorganization may affect crime similarly in both rural and urban environments. If the previous research is correct and the results are generalizable, social disorganization theory should be predictive of crime and delinquency in unique areas such as the Texas-Mexico border region. Demographically, the region is quite distinct exhibiting ecological characteristics that are extremely disadvantaged. The population is young, undereducated, and underemployed, and income levels within the region are substantially lower than the rest of the country (Peach, 1997; Fullerton, 2003). Ethnically, the area is largely Latino consisting primarily of individuals of Mexican-American heritage. Finally, the region is experiencing constant immigration and rapid population growth (Mejias, Anderson-Mejias & Carlson, 2003).

Overall, the unique characteristics of the Texas-Mexico border region make it an ideal location for further testing some of the major social disorganization tenants.

Following the conceptual modeling of previous research, this study will attempt to answer two research questions. First, do the structural factors associated with social disorganization theory predict juvenile property crime rates within the region? Second, do the relationships between the structural factors associated with social disorganization and juvenile property crime rates vary between urban and rural environments?

Chapter Three: Hypotheses, Data, and Methods

Shaw and McKay (1942) articulated that residential areas characterized by low economic status, high residential instability, and greater ethnic heterogeneity experienced higher rates of crime as a result of weakened community organization. Contemporary research has shown empirical support for Shaw and McKay's argument across a variety of urban and some rural settings. However, the Texas-Mexico border region provides a unique social setting that is characterized by variation between the region's dense urbanization and remote rural expanse. Moreover, this area is comprised of a high proportion of immigrant Latinos. The purpose of this study is to adjudicate whether the theory generalizes to this area by asking two research questions. First, do the structural factors associated with social disorganization theory predict juvenile property crime along the Texas-Mexico border? Second, are the relationships between structural factors (e.g., economic disadvantage, ethnic heterogeneity, residential instability) and crime different between urban and rural areas within the region?

Hypotheses

Social disorganization theory states that economic conditions are related to crime. Urban social disorganization research has consistently supported this contention. However, rural social disorganization research has shown mixed results for the relationships across a variety of measures (income inequality, percent poverty, percent

welfare recipients). While some rural research has shown support for the theory (Wilkinson, 1984; Arthur, 1991; Barnett & Mencken, 2002), other rural studies have failed to find significant relationships (Petee & Kowalski, 1993; Osgood & Chambers, 2000). The following relationships concerning economic conditions are hypothesized:

H1a: Per capita income will be negatively related to delinquency.

H1b: The relationship between per capita income and delinquency will not vary between rural and urban environments.

Unemployment has likewise been studied as an economic measure of social disorganization. Similar to other economic condition measures, the relationship between unemployment and social disorganization is well demonstrated within the urban literature. But, again, research in rural social disorganization has yielded inconclusive results. While some studies have found a relationship between unemployment and delinquency (Arthur, 1991; Barnett & Mencken, 2002), others have not (Osgood & Chambers, 2000). The following relationships concerning unemployment are hypothesized:

H2a: Unemployment will be positively related to delinquency.

H2b: The relationship between unemployment and delinquency will not vary between rural and urban environments.

Research into the relationship between ethnic heterogeneity and delinquency, which, again, has been largely supported in the urban literature, has found similar support in rural social disorganization research. However, there are limitations associated with these findings. Multiple studies simply operationalize ethnic heterogeneity as percent Black (Wilkinson, 1984; Arthur, 1991). Others have utilized the ethnic diversity index,

but have either calculated it considering primarily proportion White versus non-White (Osgood & Chambers, 2000) or proportion White versus proportion Black (Petee & Kowalski, 1993). The following relationships are hypothesized:

H3a: Ethnic heterogeneity will be positively related to delinquency.

H3b: The relationship between ethnic heterogeneity and delinquency will not vary between rural and urban environments.

Residential instability remains the least tested in rural social disorganization research. The studies that have included a measure of residential instability have supported the relationship with delinquency (Petee & Kowalski, 1993; Osgood & Chambers, 2000; Jobes et al., 2004). However, a number of other rural social disorganization studies have failed to include a measure of residential instability (Wilkinson, 1984; Arthur, 1991; Barnett & Mencken, 2002). The following relationships are hypothesized:

H4a: Residential instability will be positively related to delinquency.

H4b: The relationship between residential instability and delinquency will not vary between rural and urban environments.

Data

To assess the impact of social disorganization on delinquency in the Texas-Mexico border region, data were collected from seven independent sources: 1) arrest data from the Uniform Crime Reports (UCR) housed at the University of Michigan's Inter-University Consortium for Political and Social Research (ICPSR), 2) population, age, and ethnicity data from the United States Census Bureau (USCB) for the years 1990 and 2000, respectively, 3) intercensal estimates for population, age, and ethnicity from the

Texas State Data Center (TXSDC) for 1991 to 1999, and 2001 to 2007, 4) income information from the United States Bureau of Economic Analysis (USBEA), 5) unemployment rates from the United States Bureau of Labor Statistics (USBLS), 6) residential migration data from the Internal Revenue Service (IRS), and 7) urbanization data from the United States Department of Agriculture Economic Research Service (USDA ERS).

Unit of Analysis

While the typical conception of a “community” within the social disorganization literature has been the urban neighborhood, the neighborhood concept of communities is difficult to apply to sparsely-populated rural environments. For this reason, counties are commonly used when conducting rural research. Justification for treating rural counties as communities is based on the premise that rural settings have strong internal economic and governmental structures at the county level (Osgood & Chambers, 2000), and research in criminology has a history of county-level studies of crime (see, e.g., Phillips & Votey, 1975; Kowalski & Duffield, 1990; Petee & Kowalski, 1993; Kposowa & Breault, 1993; Kposowa, Breault & Hamilton, 1995; Guthrie, 1995; Osgood & Chambers, 2000; Baller, Anselin, Messner, Deane & Hawkins, 2001; Worrall & Pratt, 2004). However, it is important to note that all counties, both urban and rural, are composed of multiple distinct communities, and each of these communities vary in the level of social disorganization. Thus, the use of county-level averages results in the loss of important neighborhood-level variation. As the region being studied is characterized primarily by rural communities, guided by previous rural social disorganization research, counties are utilized as the unit of analysis. Although it is difficult to justify county-level

analysis for urban environments, the need for comparisons between rural and urban areas necessitates use of county-level analysis for urban areas as well. Therefore, this study examines 43 counties that form the Texas-Mexico border region as defined by the Texas State Legislature. Observations are made yearly for each county from 1990 to 2007 inclusive, yielding a total of 774 (43 counties x 18 years = 774) observations.

Dependent Variable

Consistent with prior social disorganization research, the dependent variable is the juvenile property crime rate. The juvenile property crime rates for each observation were generated using UCR index property crime arrest counts for juveniles aggregated to the county level. The *juvenile index property crime rate* was operationalized by calculating the arrest counts for each observation, then dividing these counts by the at-risk population and multiplying by 100,000 to generate standardized rates which can be interpreted as the number of property crimes per 100,000. Standardizing the dependent variable in this way simplifies comparisons between counties of disparate size.

Arrest data have often been used as a measure of crime by criminologists conducting community level studies (Blau & Blau, 1982; Wilkinson, 1984; Arthur, 1991; Liska & Bellair, 1995; Liska, Bellair & Logan, 1998; Steffensmeier & Haynie, 2000; Osgood & Chambers, 2000; Jacob, 2006; Cancino, Varano, Schafer & Enriquez, 2007). Use of arrest data as a measure of crime has been validated against calls for police service (Warner & Pierce, 1993), victim self-reports (Sampson, 1985; Sampson & Groves, 1989), and offender self-reports (Gottfredson, McNeil & Gottfredson, 1991; Elliot et al. 1996). However, the use of arrest data has not been specifically validated for rural areas. Since arrest practices may be less formal in rural jurisdictions due to the increased likelihood of

social ties, this measure may be less valid in rural as opposed to urban areas (Osgood & Chambers, 2000). This problem may be compounded when considering juvenile arrests. While no studies have specifically validated the use of arrest data in rural environments, based upon research by Laub (1983) and Bachman (1992), most rural social disorganization scholars have relied upon arrest data as a measure of delinquency (Wilkinson, 1984; Arthur, 1991; Petee & Kowalski, 1993; Osgood & Chambers, 2000; Barnett & Mencken, 2002). Because there is no research demonstrating superior validity of other measures (e.g. victimization surveys and calls for service) in rural environments, following previous rural social disorganization research, arrest rates are utilized in the present analysis.

Independent Variables

Per capita income, a county-level economic indicator, was derived from USBEA data. *Per capita income* was operationalized by calculating the total reported income within a county and dividing by the USCB midyear population estimates. Because per capita income is a per person measure, no additional manipulation was required for inclusion in the analysis. It is important to note that measuring economic characteristics of a county in this manner may be less reliable than the more sophisticated economic-related measures that include a combination of items, such as percent living below the poverty level, female-headed household, and race/ethnicity. While research has indicated that rates of poverty may be more important than average income (Figueroa-McDonough, 1991), data for rates of poverty for a given county are generally only available for census years. Due to the methodological design of this study, per capita income was the most appropriate measure because of the availability of yearly measures. Relying on the

USBLS data, the second county-level economic characteristic was unemployment.

Unemployment was operationalized by calculating the number of individuals over the age of 16 who are jobless and actively seeking work and dividing by the number of individuals in a county's labor force (the number of individuals that are jobless and actively seeking work plus the number of individuals that are actively employed).

Because unemployment varies throughout the year, the calculation is performed monthly and the results are averaged to generate a measure for the year.

Ethnic heterogeneity was measured by calculating the diversity index (DI) from USCB and TXSDC ethnic composition data. The diversity index is a common measure and has been used consistently by researchers as a measure of ethnic heterogeneity (Sampson & Groves, 1989; Warner & Pierce, 1993; Osgood & Chambers, 2000; Markowitz, Bellair, Liska & Lui, 2001). To operationalize *ethnic heterogeneity*, the population counts for each county were calculated for four ethnic groups (White, Black, Latino, and other). The group totals were then divided by the total population for the county yielding a proportion for each group. Then, the diversity index is mathematically calculated by:

$$DI = 1 - (\sum p_i^2)$$

where p_i is the proportion of the population of each group to the entire population (Greenberg, 1956). A score of zero (0) on the diversity index indicates true homogeneity while scores approaching one (1) indicate increasing heterogeneity. For the purpose of regression analysis, the DI is multiplied by 100 to simplify the interpretation of the regression coefficients. Regression coefficients are commonly interpreted as the expected change in the dependent variable caused by a one unit change in the independent

variable. Because the DI is bounded from zero to one, an interpretation based upon a one unit increase can be difficult to conceptualize. DI, as calculated above, is essentially a proportional measure, and multiplying it by 100 allows it to be interpreted as a percentage. As a result, regression coefficients associated with $DI*100$ can be interpreted as the expected change in the dependent variable caused by a one percent change in ethnic diversity.

Based on IRS county-level migration data, two measures (percent inflow and percent outflow) are used to represent the conception of residential instability. The IRS data are reported as county-level aggregates and include the number of residents who moved into (inflow) and out of (outflow) each county within a given year. *Percent inflow* was operationalized by calculating the number of individuals that moved into a county in a given year, dividing by the county's total population, and multiplying by 100; whereas, *percent outflow* was operationalized by calculating the number of individuals that moved out of a county for the year, dividing by the total population and multiplying by 100. Each calculation yielded a percentage which standardized the measures and simplified the interpretation of the regression results. The IRS data used to calculate the counts were generated by comparing the addresses of tax returns filed by taxpayers to those filed by the same taxpayers in the previous year. Changes in the home addresses reported by the taxpayers indicate whether their household moved within the tax year. Using the number of exemptions claimed, the IRS estimates the number of actual individuals that have moved.

Control Variables

Percent male was calculated from the USCB and the TSDC data, and was operationalized by calculating the male population and dividing by the total population. Finally, counties were measured as *urban* if they met the USDA ERS Rural/Urban Continuum Code (RUCC) 2003 metro definition. The 2003 RUCC metro definition classifies a county as metro if it contains one or more cities or urbanized areas with at least 50,000 residents. Counties lacking a city or urbanized area of 50,000 are classified as metro if they are adjacent to a metro county and more than 25% of its workforce commuting into the adjacent metro county for work. Because the USDA ERA has only published RUCC information twice (1993 and 2003), and the metro definition changed between 1993 and 2003, counties were classified according to the 2003 definitions using USCB and TXSDC population information for each year. For the purpose of analysis, *urban* was coded as a dichotomous dummy variable ($urban = 1$, $rural = 0$) using rural as the reference group.

Method of Analysis

The present study aims to analyze the relationships between delinquency and the ecological factors of social disorganization in a predominantly Latino environment. Fixed-effects panel regression is employed to model the changing ecology. Panel models are a powerful regression technique (Marvel & Moody, 2008) for the analysis of time-series data nested within several cross-sectional units (Worrall & Pratt, 2004). The units within this analysis are the observed counties, and each contains an 18 year time series (1990 to 2007). While analytically useful, panel models are complex and have several unique problems that can make estimation and interpretation difficult (Worrall & Pratt,

2004; Marvel & Moody, 2008). Due to the challenges associated with this technique, a series of steps were taken to analyze the data.

First, descriptive statistics were generated for each of the variables in the sample. The purpose of this step is twofold: (1) it provides a way to determine the appropriateness of the data for multivariate analysis, and (2) it provides a convenient way to compare the sample of this analysis to those of the past and the future. The second step consisted of analyzing the variance properties of the sample to determine the extent and effect of measurement error in the sample, which, in turn, ultimately required a reduction in the observations for the final analysis. Next, descriptive statistics were generated for the trimmed (reduced) sample for comparison to the original sample. Fourth, bivariate correlations were calculated for each of the variables. Bivariate correlations assess the uncontrolled relationships between the dependent and independent variables and help determine which variables are appropriate for inclusion in the multivariate analysis. Fifth, a number of diagnostic procedures were undertaken to assess data assumptions associated with the panel regressions. Finally, a fixed-effects panel was estimated, followed by a secondary fixed-effects panel model which included urban interactions with all the theoretical predictors.

Chapter Four: Analysis and Findings

Analysis began with descriptive and diagnostic techniques aimed at increasing confidence in the data and model estimations (i.e., fixed-effects). For example, descriptive statistics were generated for the initial sample to provide an initial look at the properties of the sample. An analysis of the variance of each county's observations for juvenile property crime rate provided a basis for observation exclusion. Descriptive statistics for the trimmed sample allowed comparison with the original sample to consider possible bias. Bivariate correlations were employed to assess the appropriateness of including particular exploratory variables in the regression analysis. Throughout the process, the relationships between the results and previous research were considered. After doing so, the analysis proceeded with the estimation of two separate fixed-effects panel models each designed to answer the proposed research questions, respectively.

Preliminary Statistics

Descriptive statistics.

The initial sample included a total of 774 total observations nested in 43 counties across 18 years. Seven of the counties were classified as urban, while the remaining 36 were rural yielding a total of 126 urban observations and 648 rural observations. Means, standard deviations, minimums and maximums were calculated for each variable for the entire sample, and the results are shown in Table 1, below. Histograms of the distributions for each variable are presented in Appendix One (Figures 2 through 8).

Table 1: Descriptive Statistics for All Observations (N = 774)

Variable	Mean	SD	Min	Max
<i>Independent Variables</i>				
Per capita income (in dollars)	16,837	5,637	5,479	39,469
Unemployment	8.54	6.31	.80	40.80
Ethnic heterogeneity	37.06	14.06	4.08	57.49
Percent inflow	5.42	2.05	0	13.19
Percent outflow	5.62	1.91	0	13.94
Percent male	49.94	1.78	46.76	64.08
<i>Dependent Variable</i>				
Juvenile property crime Rate	556.0	517.3	0	3,636

To further probe the data, descriptive statistics were generated for each individual county's 18 observations (not shown). During this phase of the diagnostic process, a substantial discrepancy was noted between the variance of the juvenile property crime rate for the smallest counties and the remaining sample. Within the region, population ranges from 350 to 1,579,414 corresponding to at-risk juvenile populations ranging from 55 to 427,904. While utilizing rates allows for direct comparisons between the counties, it does not standardize the variances between the units. Fixed-effects panel modeling does not require equal variance within each unit, but the extreme variance represented by the smallest counties raised a question concerning the potential effect of measurement error in the analysis. For example, the smallest county in the sample has an at risk population that fluctuates around 55. In this particular county, most years show no juvenile property crime arrests corresponding to a rate of zero, the minimum arrest rate for the entire sample. However, in certain years the arrest count is two, which corresponds to an arrest rate of 3636 per 100,000, the maximum arrest rate for the entire sample. The problem was noted in several counties during years with low at-risk populations. Because arrest rates are generated from arrest counts, and arrest rates are viewed within this study as a

measure of delinquency, a question is raised concerning the extent and influence of measurement error in these observations. In essence, measurement error in the counties with very small at-risk populations may affect the regression results and lead to biased estimates. As such, a number of observations in counties with extremely low populations were removed.

To justify the elimination of observations, an iterative analysis of the variance in the arrest rate was conducted to determine an appropriate cut point. Since the correlation between the at-risk population and the total population was extremely high ($r = .995$, $p < .001$), and it is easier to conceptualize counties defined by the size of their total population rather than by the size of a subset of the population (i.e., at-risk population), the analysis was conducted to find an appropriate minimum total population size. The total sample of 774 observations shows a mean arrest rate of 551.53, a median 457, and variance of 225,310.2. Observations that had a total population less than 1,000 were removed from the sample, and descriptive statistics were generated (not shown). This process was repeated several times raising the minimum population by 1,000 each time. The analysis showed that as the minimum population was increased, the mean and the median increased. The variance decreased sharply until the minimum population reached 6,000; beyond that point, the variance remained stable (the trend is shown in Figure 1, below).

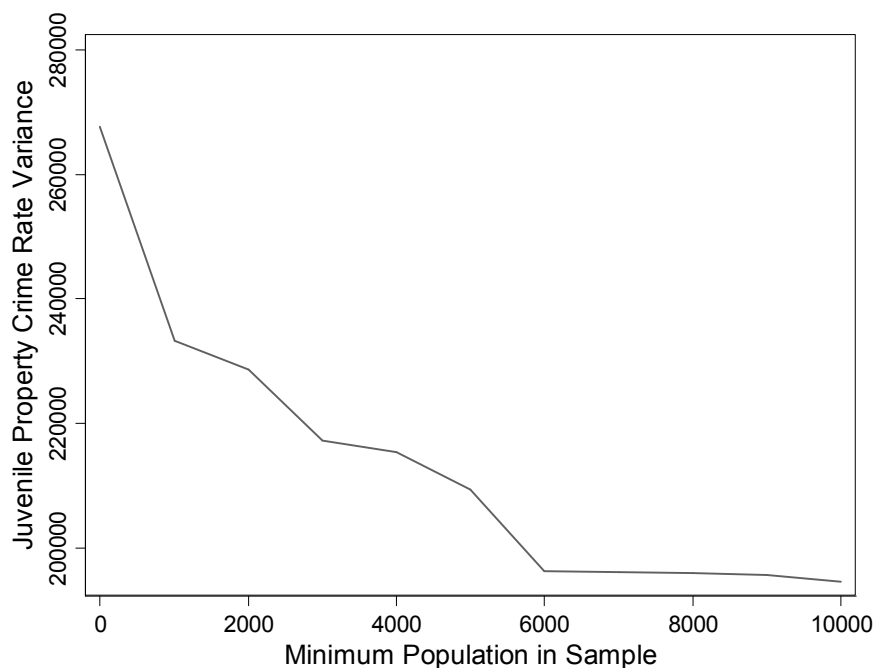


Figure 1: Variance in Juvenile Property Crime Rate by Minimum Population

Based on the variance analysis, 6,000 was chosen as the minimum population size for the remainder of the analysis leaving a total of 526 observations. Table 2 shows the descriptive statistics for the trimmed sample. Histograms of the distributions for each variable for the trimmed sample are presented in Appendix Two (Figures 9 through 15).

Table 2: Descriptive Statistics for Counties with a Minimum Population of 6,000 (N=526)

Variable	Mean	SD	Min	Max
<i>Independent Variables</i>				
Per capita income (in dollars)	16,361	5,705	5,749	38,431
Unemployment	10.16	6.94	1.7	40.80
Ethnic heterogeneity	34.54	14.98	4.20	57.49
Percent inflow	5.15	1.78	2.00	12.26
Percent outflow	5.33	1.61	2.18	13.94
Percent male	49.69	1.76	46.76	55.57
<i>Dependent Variable</i>				
Juvenile property crime Rate	614.8	438.6	0	2703

Bivariate correlations.

Using the trimmed sample, bivariate relationships were assessed by calculating correlations for each of the variables. The results are presented in Table 3 (below). All of the predictors were significantly related to the juvenile property crime rate except per capita income and percent outflow. Consistent with prior research, both unemployment (.105) and ethnic heterogeneity (.090) were positively related to property crime. As expected, percent inflow was positively (.117) related to the outcome. Unexpectedly, however, percent male (-.380) was negatively related to juvenile property crime rate. Analysis of the county by county descriptive statistics indicated that the negative relationship may be a result of an unequal distribution of the male population between counties. While the effect of the between-county distribution of percent male might affect the results of any fully-pooled analysis (such as bivariate correlations), it is unlikely that they will affect on the fixed-effects panel models. The significance of the relationships between juvenile property crime and unemployment, ethnic heterogeneity, percent inflow, and percent male indicated that these variables were appropriate for inclusion in

the multivariate models. Per capita income, while not significant, was negatively related (-.038) as expected. Although failing to reach statistical significance, per capita income was included in the multivariate model due to its theoretical importance. Contrary to expectation, percent outflow, also insignificant, was negatively related (-.015) to juvenile property crime rate. The weakness of the correlation calls into question the actual direction of the relationship, but another correlation, the correlation between percent inflow and percent outflow (.752, $p \leq .001$), suggested that percent outflow should be included in the multivariate analysis. Because percent inflow and percent outflow represent two measures of residential instability, it is important to consider their conceptual independence associated with the outcome. Counties experiencing both high inflow and high outflow are, in fact, more transitional than those which are high on one measure and not the other. These 'transitional' counties are less stable than counties only experiencing one or the other. Distinguishing between the effect of population inflow and outflow is important for developing a more concise understanding of residential instability. As such, percent outflow was included in the multivariate analysis on theoretical grounds.

Table 3: Bivariate Correlation Coefficients (N=526)

Measures	(1)	(2)	(3)	(4)	(5)	(6)
1) Juvenile property crime rate	1.00					
2) Per capita income	-.038	1.00				
3) Unemployment	.105*	-.662***	1.00			
4) Ethnic heterogeneity	.090*	.412***	-.573***	1.00		
5) Percent inflow	.117**	.193***	-.210***	.477***	1.00	
6) Percent outflow	-.015	-.028	-.023	.394***	.752***	1.00
7) Percent male	-.380***	.034	-.233***	.349***	-.043	.096*

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$

Model diagnostics.

After assessing the univariate and bivariate relationships, the analysis continued by considering three other potential data problems which might bias the regression results: 1) nested observations, 2) time-series concerns, and 3) outliers. Because the counties were measured annually over 18 years, the yearly observations are nested within counties. When observations are nested within units, the observations are likely more similar (than different) within a given unit which violates the standard OLS assumption of independence. The nested nature of the data also yielded residual distributions that violated the OLS assumption of homoskedasticity or equal conditional variance of the error term. The choice of a fixed-effects panel model in lieu of an OLS regression model provided a way to correct for the nested nature of the data. The fixed-effects panel model assumes that the relationship between the predictors and the dependent variable is the same across units, but each unit within the regression model has its own intercept. In this way, the fixed-effects panel model allows each unit to be different in its crime rate while estimating effects of predictors for the full model.

While most social disorganization research is cross-sectional, the current study contributes to the literature by conducting a time-series analysis. However, the time-series nature of the data is important to consider because it can cause substantial issues in regression analysis when the dependent variable is non-stationary. Stationarity implies that the variable has a true mean which it tends to return to over time (i.e., reversion to the mean). A variable that is non-stationary trends over time either generally increasing or decreasing. While a mean can be calculated for a non-stationary variable, it carries no interpretative value. If other variables trend across time as well, any correlation based

analysis will indicate a relationship. However, the possibility that the relationship is spurious is much higher than in cross-sectional data because it can result from the fact that both variables are non-stationary. For the present analysis, stationarity in the dependent variable was assessed using Im, Pesaran, and Shin's (2003) panel adaptation of the Dickey-Fuller unit root test. The test, which assumes a unit root under the null hypothesis ($H_0 =$ the series is non-stationary), showed that the juvenile property crime rate did not have a unit root ($t\text{-bar} = -2.372, p < .001$) and was stationary. Additionally, the model was analyzed for the presence of serial autocorrelation, a related time-series problem, using the Drukker (2003) and Wooldridge's (2002) test for autocorrelation. The test assumes no autocorrelation under the null hypothesis and showed no serial autocorrelation in the model ($F_{(1, 42)} = 1.146$ and $p = .2905$).

The final issue with the data was the presence of outliers. Using Hadi's (1992, 1994) method for detection of outliers in multivariate models, 17 outliers were identified at $p < .05$. They were removed from the sample leaving a total of 509 observations. After removing these outliers, the analysis proceeded with the estimation of the multivariate models.

Multivariate Analysis

After completion of the diagnostic procedure, two fixed-effects panel models were estimated to assess the relationships between the juvenile property crime rate and the predictors using the remaining 509 observations. The first model, which included per capita income, unemployment, ethnic heterogeneity, percent inflow, percent outflow, and percent male, tests the relationship between the structural factors of social disorganization and delinquency to evaluate the applicability of the theory to the Texas-Mexico border

region. The second fixed-effects panel model included predictors from the first model but also included interaction terms between urban and per capita income, urban and unemployment, urban and ethnic heterogeneity, urban and percent inflow, and urban and percent outflow. Inclusion of interaction terms between urban and the theoretical predictors tests the hypotheses that the relationships between the structural factors of social disorganization do not change between urban and rural settings.

Panel model one: Main effects only.

The results of the first fixed-effects panel model are presented in Table 4, below. Overall, The model was significant ($F_{(6, 473)} = 44.17, p < .001$) and explained 35.91% of the within-unit variance. All predictors were in the hypothesized direction. However, only per capita income (-.035), ethnic heterogeneity (13.50), percent inflow (57.80), and percent male (55.84) reached statistical significance in relation to juvenile property crime. Unemployment rate (2.75) and percentage outflow (29.99), while in the expected directions, failed to achieve significance with the outcome. Per capita income had the largest individual effect (Beta = -.381), and ethnic heterogeneity index had the second largest individual effect (Beta = .367). Collinearity was assessed to determine its impact on the regression estimates by calculating variance inflation factors (VIF), and the results are presented in Table 5. Based upon the VIF statistics, collinearity was determined to not bias the regression estimates.

Table 4: Model One - Fixed Effects Panel Model for Juvenile Property Crime Rate (N=509)

Predictor	Coefficient	SE	Beta
Per capita income	-.035***	.004	-.381
Unemployment	2.75	4.07	.034
Ethnic heterogeneity	13.50*	6.33	.367
Percent inflow	57.80**	18.98	.229
Percent outflow	29.99	22.72	.111
Percent male	55.84**	14.44	.193

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$ $F_{(6, 473)} = 44.17, p < .001, \text{Within } R^2 = .3591$

Table 5: Multicollinearity Analysis

Independent variable	VIF
Per capita income	1.55
Unemployment	1.98
Ethnic heterogeneity	1.82
Percent inflow	2.49
Percent outflow	2.54
Percent male	1.19
Mean VIF	1.93

In general, results from the first panel model are consistent with the tenants of classical and contemporary social disorganization research. Within the sample, as per capita income increases, juvenile property crime rate decreases. This trend reflects Shaw & McKay's (1942) original contention that communities without sufficient resources lack the capacity to develop informal social control resulting in increased crime and delinquency and represents a similar finding to the results of previous urban and rural social disorganization scholars (Sampson & Groves, 1989; Chamlin, 1989; Warner & Roundtree, 1997; Bellair, 2000; Kubrin, 2000; Osgood & Chambers, 2000). The results for unemployment are less conclusive. Within the sample, as unemployment increased, the crime rate increased consistent with some prior research (Arthur, 1991; Barnett & Mencken, 2002). However, as in other studies (Osgood & Chambers, 2000), the results

lacked statistical significance which raises questions whether the results would be replicated in future analyses.

The observed positive relationship between ethnic heterogeneity is consistent with both theory and previous research (Wilkinson, 1984; Arthur, 1991; Petee & Kowalski, 1993; Warner & Pierce, 1993; Warner & Roundtree, 1997; Kubrin, 2000; Osgood & Chambers, 2002; Jobes et al., 2004), and indicates the theorized effects of ethnic heterogeneity apply within the region. This again reflects Shaw and McKay's (1942) contention that social organization is difficult to achieve in an environment of conflicting cultural differences. The observed results for percent inflow and percent outflow were both consistent with theory and previous research on residential instability (Sampson & Groves, 1989; Petee & Kowalski, 1993; Warner & Roundtree, 1997; Bellair, 2000; Kubrin, 2000; Osgood & Chambers, 2000; Jobes et al., 2004). These findings, once more, support Shaw & McKay's (1942) original realization that communities characterized by influx and exodus of residents lack the necessary stability to establish community relationships needed to exert informal social control. However, the larger effect size of percent inflow (Beta = .229) indicates that newer residents entering may have a larger effect on social disorganization than members of a community leaving. While Wilson (1987) argues that the effects of population loss are related to social disorganization, it is possible that the process of social decay due to population outflow takes substantially longer to have an impact than the immediate effect of new residents moving into an area.

Panel model two: Main and interaction effects.

The results of the second model are presented in Table 6, below. Overall, the interaction model was significant and explained 38.89% of the within-unit variance. The

main effects within the second model did not vary substantively from Model 1 (see Table 4 above). Per capita income (-.026) remained significant and negative while ethnic heterogeneity (15.71), percentage inflow (65.03), and percentage male (52.40) were still significant and positive. Unemployment rate (3.20) and percentage outflow (36.95) remained insignificant. Among the interaction terms included in the second model, only the interaction between per capita income and urban was significant. The relationship was negative (-.033) and represented the largest individual effect in the model (Beta = -.448). Again, the ethnic heterogeneity index had the second largest individual effect (Beta = .427).

Table 6: Model Two - Fixed Effects Panel Model for Juvenile Property Crime Rate with Interaction Terms (N=509)

Predictor	Coefficient	SE	Beta
Per capita income	-.026***	.004	-.283
Per capita income*Urban interaction	-.033***	.008	-.448
Unemployment	3.20	4.35	.039
Unemployment*Urban interaction	3.31	11.74	.024
Ethnic heterogeneity	15.71*	7.27	.427
Ethnic heterogeneity*Urban interaction	-27.37	16.23	-.512
Percent inflow	65.03**	19.85	.257
Percent inflow*Urban interaction	-26.54	58.70	-.088
Percent outflow	36.95	23.99	.137
Percent outflow*Urban interaction	30.96	71.42	.103
Percent male	52.40*	14.39	.181

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$ $F_{(11, 468)} = 27.08, p < .001, \text{ Within } R^2 = .3889$

The significant interaction between urban and per capita income suggests that economic conditions, while affecting social disorganization in both rural and urban areas, seems to reveal a different impact in each environment. In fact, the results suggest that the negative relationship between per capita income and crime in urban environments (per capita*urban = -.033), is much larger than in rural environments. Shaw and MaKay

(1942) argued that communities without sufficient resources lack the capacity to develop social organizations effectively limiting citizen's interactions with one another through meaningful social institutions. Because interactions in rural counties have been shown to actuate primarily through kinship networks rather than through friendship networks (Kasarda & Janowitz, 1974), the potential impact of community developed social institutions may be lessened in rural environments. The insignificant interactions with the remaining theoretical predictors make it difficult to draw conclusions concerning their relationships across the urban/rural divide. However, it can be noted that, within the sample, unemployment had a larger effect in urban counties (unemployment*urban = 3.31), ethnic heterogeneity had a larger effect in rural counties (ethnic heterogeneity*urban = -27.73), percent inflow had a larger effect in rural counties (percent inflow*urban = -26.54), while percent outflow had a larger effect in urban counties (percent outflow*urban = 30.96).

Chapter Five: Conclusion

The current study has considered the fundamental precepts of social disorganization theory in the Texas-Mexico border region. It was unclear whether the effects of economic disadvantage, ethnic heterogeneity, and residential instability (measured as percent inflow and percent outflow) would have a significant relationship with delinquency in the region due to the prevalence of Latino culture and the effects of immigration. While the area is generally disadvantaged (Peach, 1997; Fullerton, 2003), previous research has suggested that immigration may serve to revitalize poor Latino areas, strengthening informal social control and establishing new community institutions (Buriel et al., 1982), which should reduce the likelihood of crime. Because the mechanisms of social control are believed to be distinct from social disorganization itself (Shaw & McKay, 1969), the relevance of the effects of Latino immigration on social control should be clear. While social disorganization theory suggests that immigration should undermine social control, Latino immigrants may import cultural values that moderate the relationships between structural factors and delinquency. To explore this paradox, research must move past the White/Black urban focus and test social disorganization theory in new areas. The findings of the present study, while consistent with the majority of previous social disorganization research, represent a step in that direction. The analysis showed that the structural factors of classic social disorganization

theory were in fact predictive of delinquency in the region despite the pervasiveness of Latino culture and immigration.

Interpreting the negative association between per capita income and delinquency is straightforward. Areas with higher overall incomes are composed of individuals with a greater financial stake in the community. Access to additional resources allows the development of meaningful social institutions, which fosters the development of informal networks that generate social control. The significant interaction term between per capita income and urban suggests that this relationship is stronger in urban environments which may be due to the varying nature of social interaction in urban versus rural settings. This may reflect the simple fact that rural social networks are based primarily upon kinship linkages, whereas urban social networks are generally based upon friendships. These friendships tend to derive from social institutions, so the development of additional social institutions is more likely to promote social control in urban settings. The kinship-based networks found in rural environments likely benefit less from the development of new social institutions due to their limited impact on kinship networks.

The observed association between ethnic heterogeneity and delinquency supports one of the main themes of social disorganization theory. Although consistent with past research, this finding adds to the understanding of the theory, because, previously, it was unclear whether this relationship would manifest itself in environments that were predominantly Latino. The Texas border region is unique in that it is described as a majority-minority area, with Latinos making up the numeric majority. The hyper focus on the relationship between Blacks and Whites in the social disorganization literature provides little insight as to how the effects of high ethnic heterogeneity would manifest

themselves in such a place. It likewise suggests that, although there may be characteristics implicit in the Latino culture that buffer against delinquency, the effects of inter-group interaction may negate this buffer in areas that are highly heterogeneous. The non-significant effect for the interaction between ethnic heterogeneity and urban clearly suggests that the relationship between ethnic heterogeneity and delinquency is similar regardless of urbanization.

The analysis supported the relationship between residential instability and delinquency. However, the multifactor approach to measuring residential instability (inflow and outflow) provides insight into the specific effects of community intrusion by new individuals and social degradation resulting from loss of community members. While a significant relationship was found for inflow related to delinquency, the analysis failed to find a significant relationship between outflow and delinquency. It is likely that these observations stem from the fact that the effects of new residents are immediate compared to the long term effects of losing community members. It is also important to note that, while not significant, the relationship between outflow and delinquency was observed to be positive. Additional testing of these measures are necessary in order to isolate their individual contributions to social disorganization. As with ethnic heterogeneity, the non-significance of the urban interactions for both inflow and outflow suggest that urbanization does not substantively alter the relationship between either measure and delinquency.

In general, the results of the present analysis suggest that social disorganization operates within the Texas border region in a manner consistent with both the theory and previous research. The relationships between structural factors and delinquency mirror

those in areas that are non-Latino, areas not characterized by high levels of foreign immigrants, and in areas of greater urbanization. The longitudinal aspect of the analysis supports the idea that temporal changes in the structural factors of social disorganization due to shifting ecology have an impact on delinquency. In this way, the results of the present analysis speak to one of the most common critiques of previous social disorganization research. Finally, the pooled nature of the analysis suggests that the relationships are likely generalizable to similar regions across the Southwestern United States.

While the present analysis has moved in a new direction by testing social disorganization in a predominantly Latino region characterized by high immigration across the urban/rural divide, a number of limitations are noteworthy. The first substantial limitation concerns using counties as the unit of analysis. While consistent with prior research, it is clear that counties are not the ideal unit for conducting social disorganization research. All counties are composed of unique communities, and each of these communities varies in terms of their levels of social disorganization and delinquency. The substantial variation found within these communities is lost when factors are measured at the county level, and this problem increases as counties move across the continuum from rural to urban. The desire to compare between urban and rural environments necessitated the use of county level measure because rural environments are difficult to assess at lower levels. Future research should address this concern by testing social disorganization theory in similar environments at lower levels of aggregation.

Other limitations concern the measures of social disorganization. First, it is unclear whether per capita income actually measures economic disadvantage as predicted by the theory. The distribution of income within a community may have more to do with the impact of economic conditions on delinquency than net income. As with the previous limitation, the loss of variation represented by using this simplified measure requires further analysis. Second, measuring ethnic heterogeneity using the diversity index, while consistent with previous research, provides insufficient insight into the relationship between heterogeneity and proportion Latino. Unfortunately, collinearity between the diversity index and proportion Latino made it impossible to analyze both factors. Third, while percent inflow and percent outflow represent promising new measures of residential instability capable of more precisely accessing the processes of social change, the measures themselves demand testing to determine the validity associated with using each.

The final limitation concerns the region itself. While substantial variation exists within the region in regard to both the structural factors of social disorganization and delinquency, the region appears quite homogenous across most of the measures when compared against other regions. The current study provides insight into the nature of social disorganization in a predominantly Latino environment, but it fails to describe any specific variation from areas that are not predominantly Latino. To understand this important variation, it is necessary to abandon the myopic gaze of regional analysis, and conduct analyses in areas which, while containing Latino populations, exhibit greater ethnic and social diversity than the variation seen in the Texas-Mexico border region.

Appendix One

Histograms for Original Sample

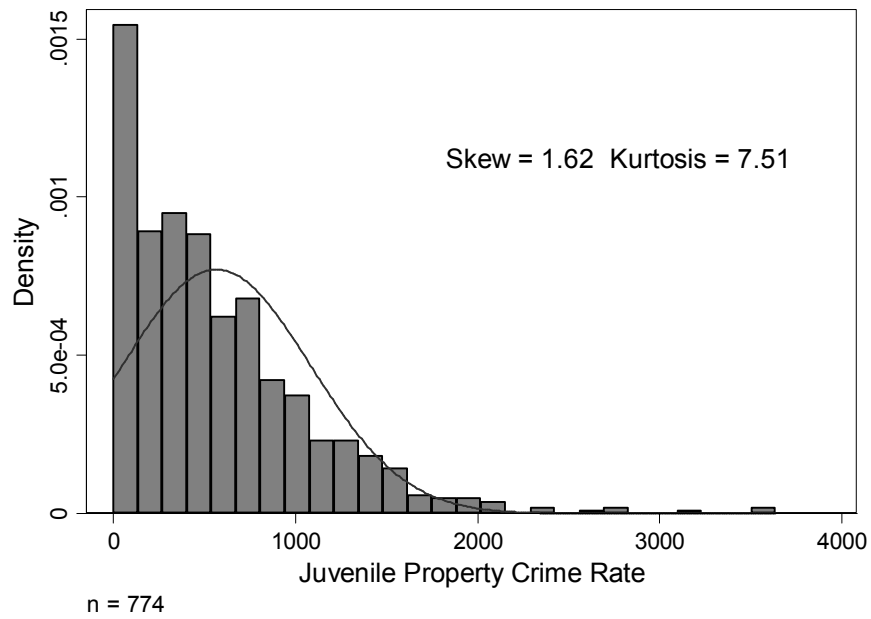


Figure 2: Distribution of Juvenile Property Crime Rate

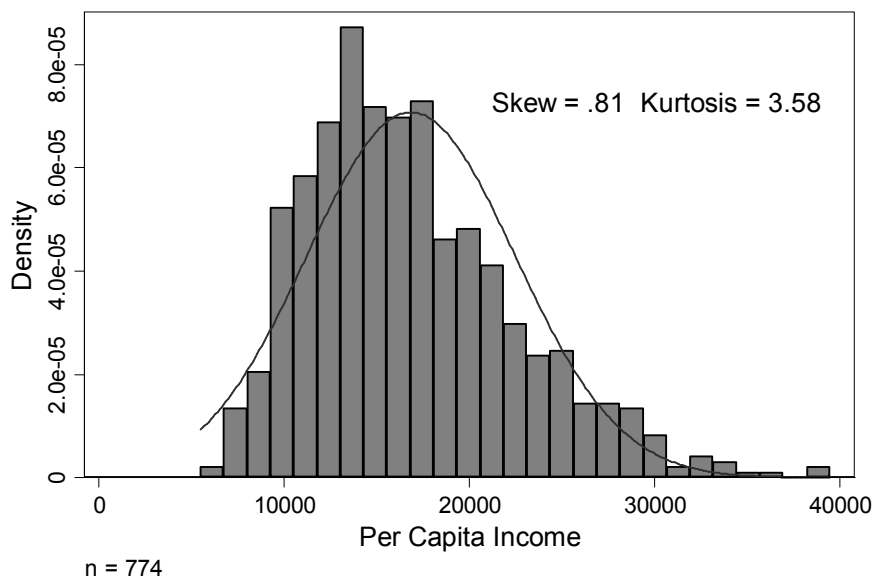


Figure 3 Distribution of Per Capita Income

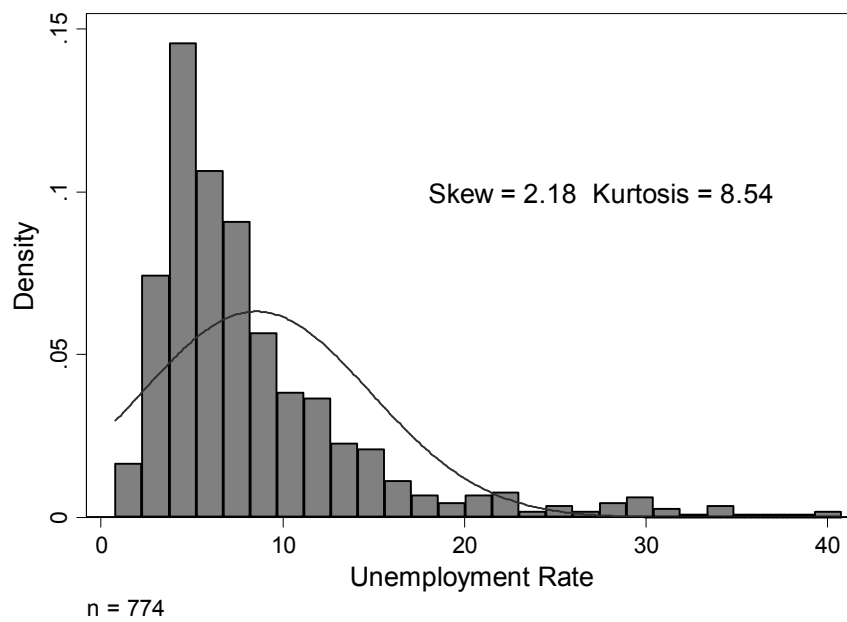


Figure 4: Distribution of Unemployment Rate

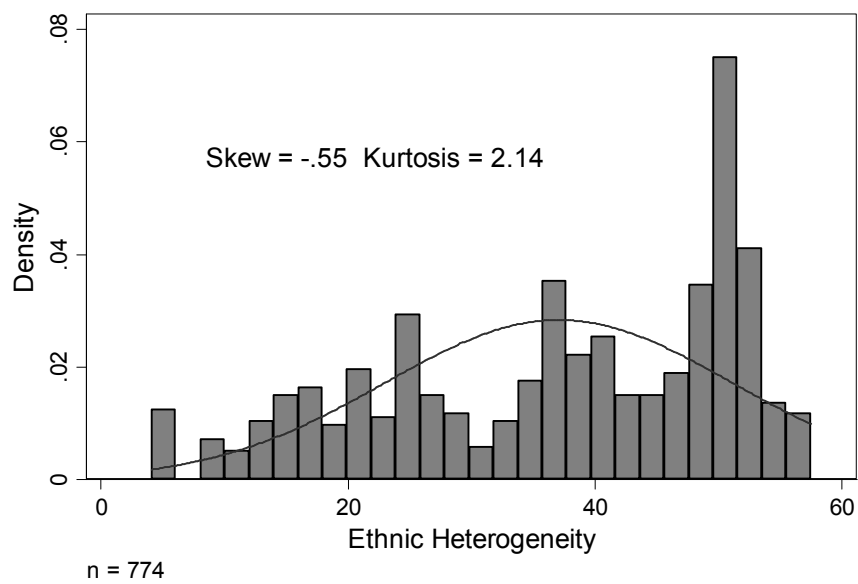


Figure 5: Distribution of Ethnic Heterogeneity

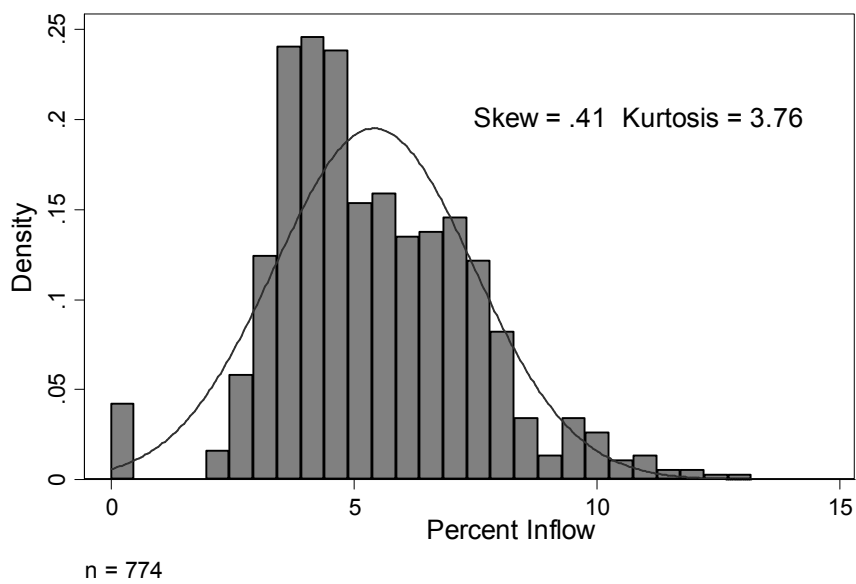


Figure 6: Distribution of Percent Inflow

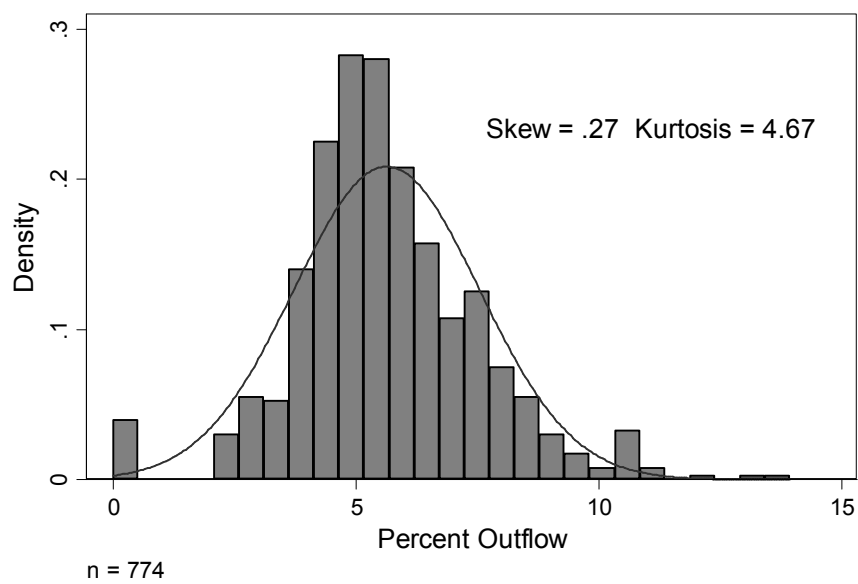


Figure 7: Distribution of Percent Outflow

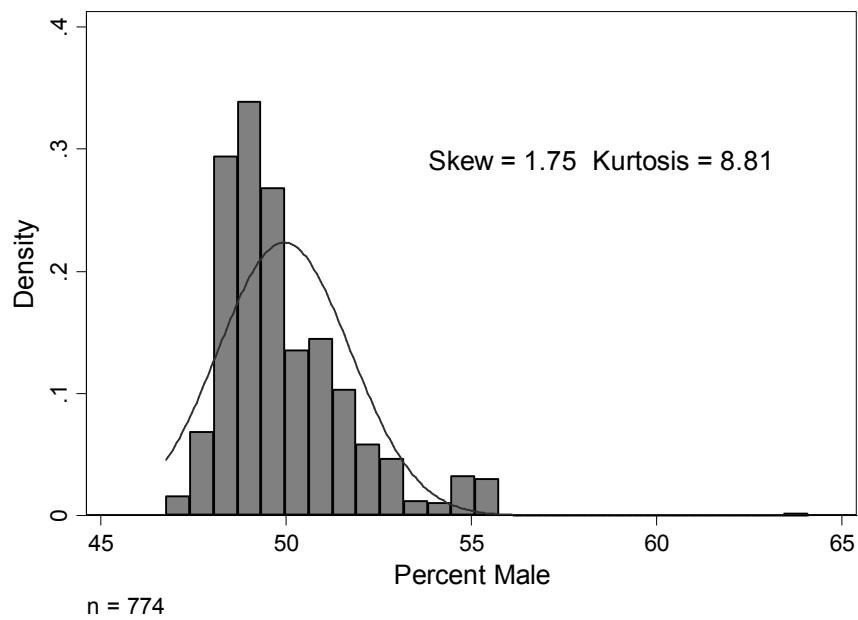


Figure 8: Distribution of Percent Male

Appendix Two

Histograms for Trimmed Sample

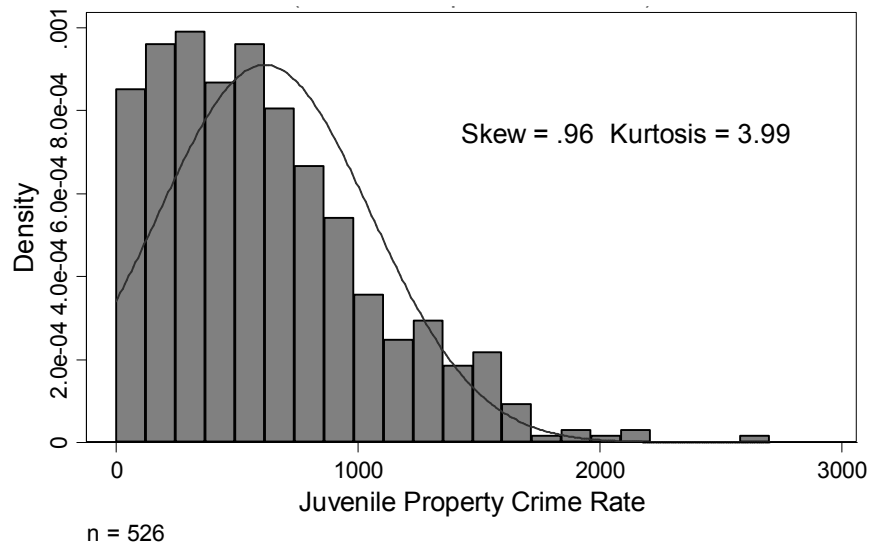


Figure 9: Distribution of Juvenile Property Crime Rate
(Minimum Population = 6,000)

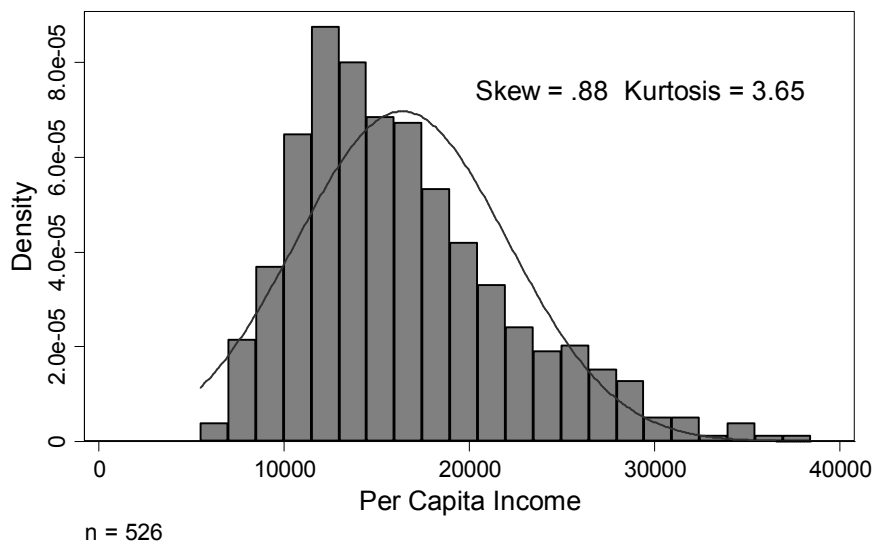


Figure 10: Distribution of Per Capita Income
(Minimum Population = 6,000)

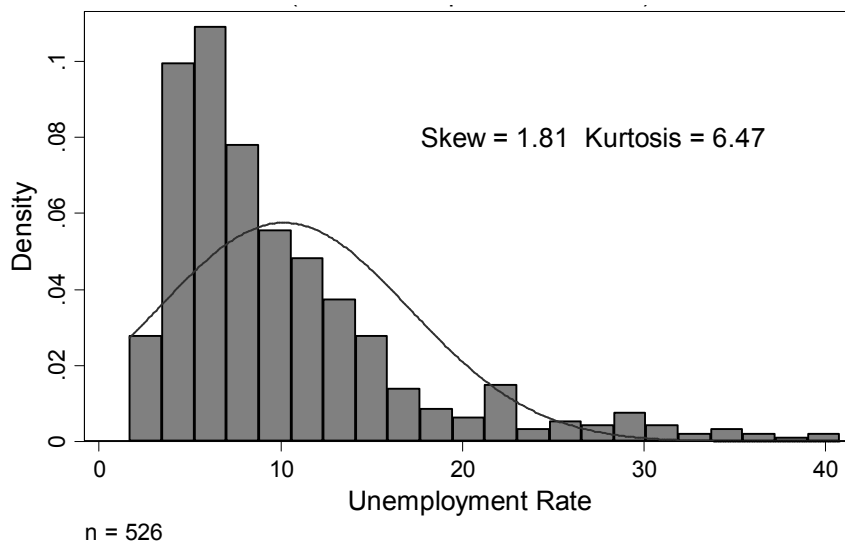


Figure 11: Distribution of Unemployment Rate
(Minimum Population = 6,000)

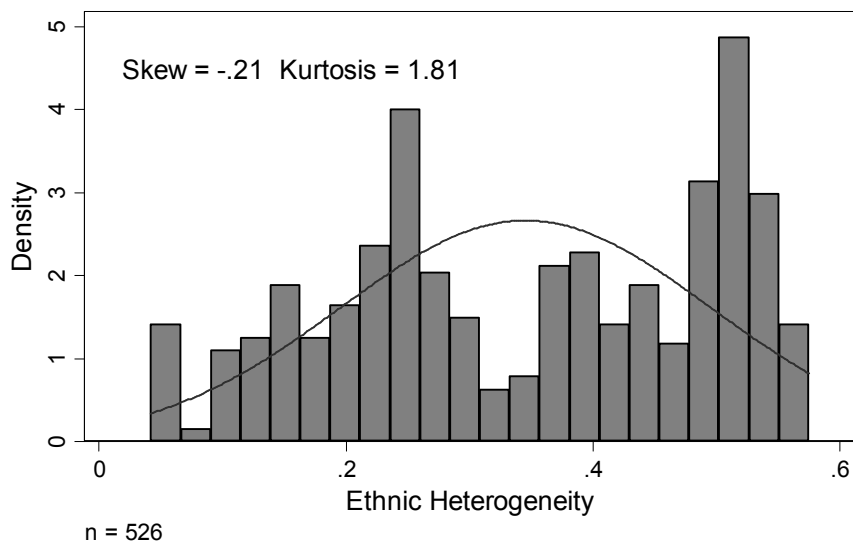


Figure 12: Distribution of Ethnic Heterogeneity
(Minimum Population = 6,000)

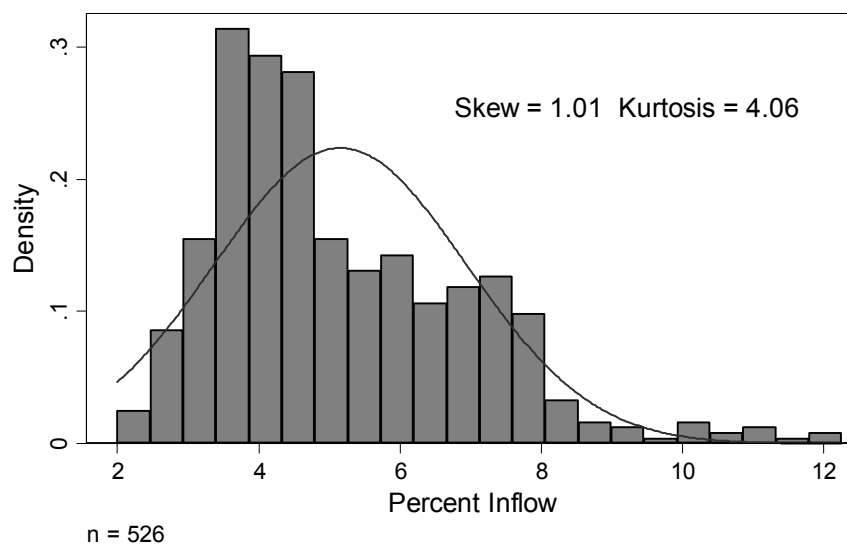


Figure 13: Distribution of Percent Inflow
(Minimum Population = 6,000)

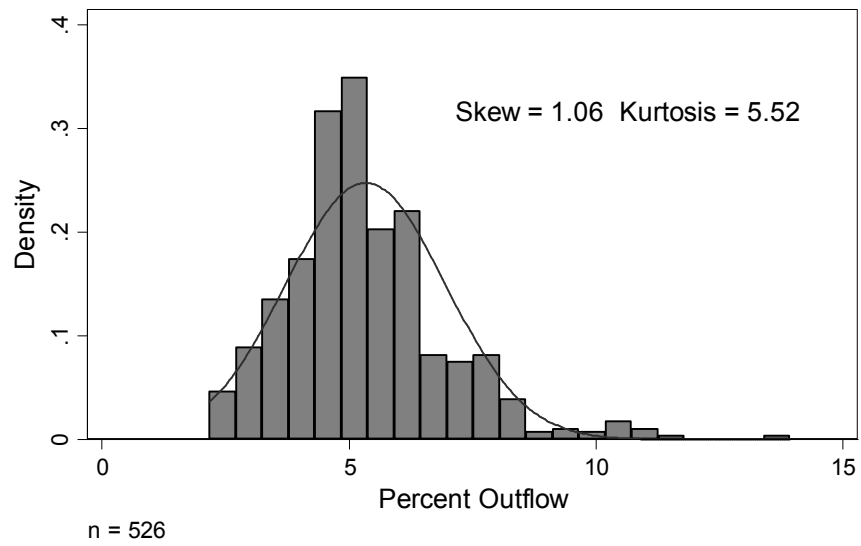


Figure 14: Distribution of Percent Outflow
(Minimum Population = 6,000)

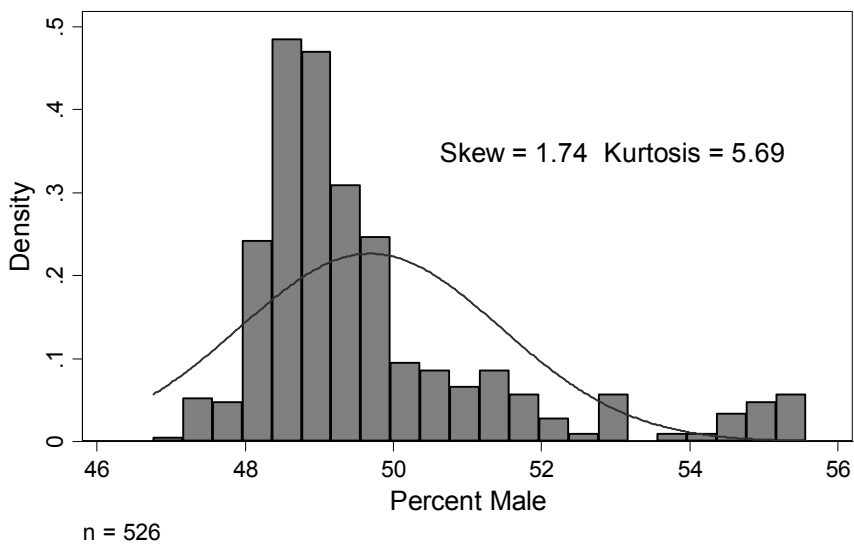


Figure 15: Distribution of Percent Male
(Minimum Population = 6,000)

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