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A Spatial Analysis Test of Decennial Crime Patterns in the United States

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A SPATIAL ANALYSIS TEST OF DECENNIAL CRIME PATTERNS IN THE UNITED STATES

By

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ABSTRACT

A Spatial Analysis Test of Decennial Crime Patterns in the United States

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Crime in the United States has steadily been decreasing since the 1990s. Social disorganization theory states that breakdowns of social institutions were the root causes of juvenile delinquency. Using exogenous variables of poverty, residential mobility, and ethnic heterogeneity, this study aims to investigate the impacts and magnitude of these variables on violent and property crime committed in the United States for adults and for juveniles. By comparing adult crime rates to juvenile delinquency rates, these findings will guide policy makers to develop effective policy tools that will provide a safer environment for the community. Using annual crime datasets, this thesis looks at decennial years 1990, 2000, and 2010 in the United States at the county level. Identified spatial effects through exploratory spatial data analysis (ESDA) are used to test on their temporal stability. A set of spatial regression models was developed to estimate the impacts of socioeconomic factors and spatial neighborhood effects on adult crimes and juvenile delinquency rates. Results from this study show crime concentrations and spatial shifts over time and where the greatest concentrations of crime were.

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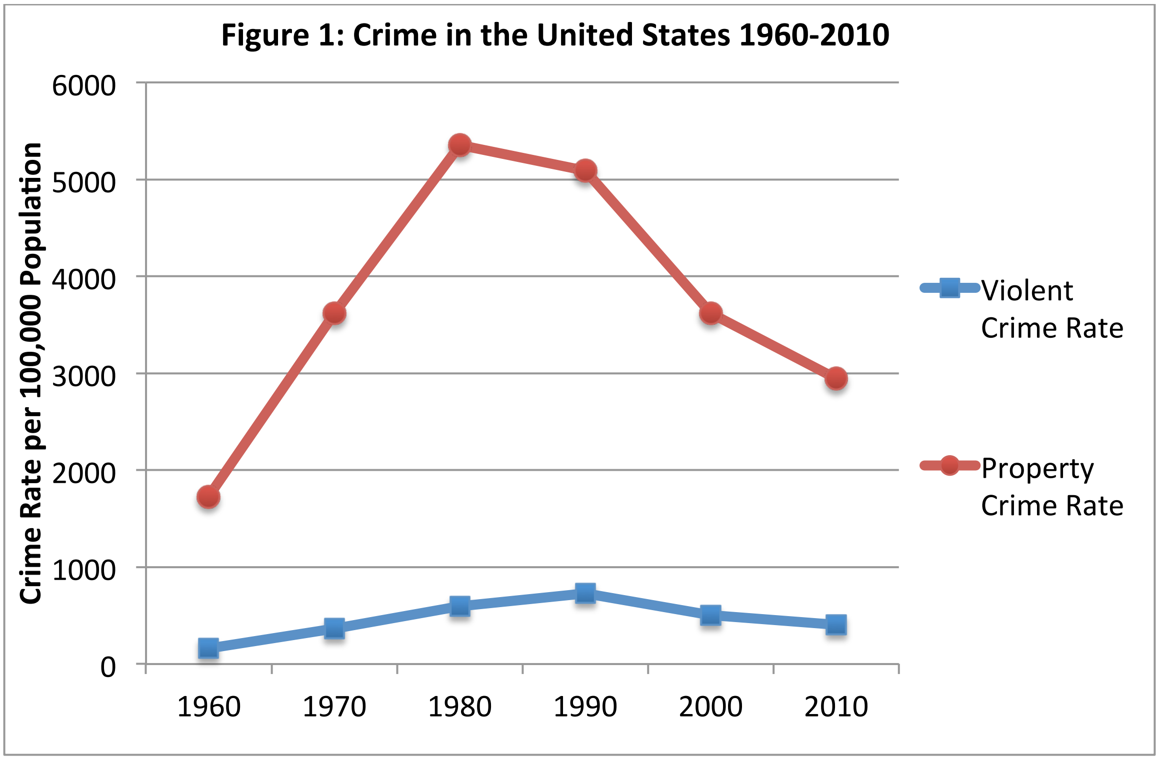
CHAPTER 1

INTRODUCTION

Since the 1990s, crime in the United States has been decreasing. According to the FBI (2011), crime rates now mirror those of the 1960s. As seen in Figure 1, although crime rates do not mirror those of the 1960s exactly, there has been a steady decline over time. Even though crime has been decreasing as a whole throughout the United States, there may be variations in the spatial distribution in where crime is being committed. Higher levels of violent crime and property crime have been concentrated in or near metropolitan statistical areas, but when studying suburban cities outside of a metropolitan statistical area, violent crime was lower but property crime was higher. Also, when looking at rural areas, both violent crime and property crime were low. Crime also seems to be higher on the coastlines of the United States when broken up into regional areas. Although crime rates have been decreasing in the United States, the total amount of crimes being committed was still the highest when compared to previous years. The United States was probably one of the most highly urbanized countries among advanced nations and yet crime was still being committed. As previously mentioned, there seemed to be areas where crime was being committed more than other places.

Since the 1990s, there has been about a 10% decrease in the number of violent crime that was being committed and about a 15% decrease in the number of property that was being committed (FBI, 2010). There were many reasons why crime was down and researchers have found correlations between variables attributed to the crime decrease. For example, according to Kneebone and Rafael (2011), crime has been declining because of improved policies. This included various education and training programs for law enforcement personnel and the use of upgraded technology. Also, there has been advancement in strategies that law enforcement agencies used, namely sophisticated software used to plot where criminals lived and where they were committing their crimes.



This study looked at spatial aspects of violent and property crime rates at the county level in the United States for adults and juveniles. By incorporating socioeconomic data, this paper attempted to see how these variables affected crime in different areas of the United States. It also provided an analysis of crime rates occurring away from metropolitan statistical areas (MSAs). Not only did this analysis allow us to look at all of the metropolitan statistical areas at once on the global level, but crime rates at the local level were also looked at to see how neighboring counties affected each other. By running spatial regressions, the results showed how each county affected one another with different socioeconomic variables. Overall, the purpose of this study was to look at the temporal and spatial behavior of crime. This study employed the spatial analytical tool of exploratory spatial data analysis (ESDA) and spatial regression models through GeoDa to test the spatial effect based on previous research done with social disorganization theory.

In order to accomplish this, social disorganization theory was used as a starting point. Social disorganization theory has initially been used to test crimes rates occurring throughout the ever-growing cities in the United States, specifically in Chicago, to see how cities were developing. Over the years, social disorganization theory has seen many expansions, including family disruption and collective efficacy, to try to explain why crime was being committed in a better and clearer way. For the purposes of this study, the original version of social disorganization theory by Shaw and McKay (1942) was used. Based on the three variables that they found were important (ethnic heterogeneity, socioeconomic status, and residential mobility), this study used spatial analysis to see whether these variables remained significant when taking into account spatial neighborhood effects.

Currently, there are many articles that analyze crime rates in major cities, specifically Chicago, but do not take into account other smaller cities in the United States that may have their own unique patterns which leads to limitations in policies. Since these studies were only looking at one specific city, they were analyzing data at the census tract or census block level. This did not give a broader picture of what the entire United States looked like. Although their findings were interesting and significant, they may not be able to transfer the results to smaller cities. This paper aimed to change that through a comprehensive study of all counties in the entire United States and applying the same model for all metropolitan statistical area cities. By doing this, this paper may be able to show unique patterns that have not been shown in previous major city studies.

Organization of the Paper

Chapter 2 will describe the basic principle of social disorganization theory. It will then be followed by a review of previous studies that have either used this theory as an interpretive framework or tested its validity. Also included will be a literature review of previous studies that have utilized spatial analysis, specifically exploratory spatial data analysis, in their own studies. Chapter 3 will state the research questions and hypotheses, and then describe the data sources and data collection procedures. Independent and dependent variables along with the analytical techniques will also be described. Chapter 4 will analyze the spatial distribution of crimes using exploratory spatial data analysis and spatial regression models with GeoDa. Chapter 5 will summarize the results from this study and discuss major implications derived from this study.

CHAPTER 2

LITERATURE REVIEW ON SOCIAL DISORGANIZATION AND SPATIAL ANALYSIS

Social Disorganization

Social disorganization theory relates many community and social factors as to why crime and delinquency occur. Exogenous sources of social disorganization include socioeconomic status, residential mobility, heterogeneity, family disruption, and urbanization. Intervening dimensions of social disorganization include the ability of a community to supervise and control teenage peer groups, local friendship networks, and local participation in formal and voluntary organizations. Together these exogenous sources and intervening dimensions tried to explain why crime and delinquency were prevalent.

Clifford Shaw and Henry McKay first developed Social Disorganization Theory in 1942. Their ideas were based off of the work done by Robert Park and Ernest Burgess published in 1925. It was in Chicago that this particular school was developed because of the sheer number of people that were moving there and how fast this city was expanding. This was during a time when African Americans were moving North to find a better life away from slavery and Europeans were immigrating to America. Scholars at the University of Chicago believed that it was in studying the traits of the neighborhood that would allow researchers to understand why crime was being committed compared to other theories that looked at individual level factors attributed to personality (Cullen & Agnew, 2010). Park and Burgess studied the way in which cities developed, specifically Chicago, and thought of these cities as living organisms. Their model was called the

Concentric Zone Model. The first zone was considered to be where all of the factories and businesses were in the city center. The second zone was labeled the zone in transition. People who settled in this zone tended to be immigrants and worked in the factories in the city center. Housing in this area was cheap but also run down. Once families had enough money, they would move out of the zone in transition to the zone of workingman's homes. As with previous zones, people would leave the current zone they were living in to the move to the outskirts of the city where the residential zone and commuter's zones were. This last zone was considered the suburbs (Park, Burgess, & McKenzie, 1925).

Shaw and McKay believed that they could use Park and Burgess' Concentric Zone Model to relate it to delinquency. They plotted all of the home addresses of the juvenile delinquents to see what zone they lived in. Shaw and McKay hypothesized that delinquency would be higher in the zone in transition, where social disorganization was more prevalent, and lower in neighborhoods that were more affluent and stable. Social disorganization was defined as the "inability of community members to achieve shared values or to solve jointly experienced problems" (Shaw & McKay, 1942). They found that the highest concentrations of crime were in the zone in transition. They believed that the makeup of the community was what was causing crime, not the type of people living there. It did not matter the type of people that were living in the community because crime rates stayed high regardless of population makeup. They found that three factors contributed to higher rates of delinquency and to social disorganization: poverty, ethnic heterogeneity, and residential mobility. If all three of these factors were high in the community, then they hypothesized delinquency would be high as well. Overall, they found that crime rates stayed relatively stable in the area that they were studying (Shaw & McKay, 1942).

Social Disorganization Theory tried to explain how community factors would have an effect on crime. It was defined as the inability of a community structure to realize the common values of its residents and maintain effective social controls. It was based on Shaw and McKay's 1942 research which found that there were three intervening dimensions of social disorganization: ability of a community to supervise and control teenage peer groups, local friendship networks, and local participation in formal and voluntary organizations. They hypothesized that three neighborhood scale variables (economic status, ethnic heterogeneity, and residential mobility) form social disorganization and contribute to increased rates of juvenile delinquency.

Since Shaw and McKay developed their theory in 1942, there have been many studies that have tested this theory and its applicability to society. Many researchers have found support for social disorganization theory but also there have been studies that have not found support for social disorganization theory. For a short time social disorganization theory was not popular and there were many scholars who were going away from the Chicago School toward other theories, but by the 1980s social disorganization theory caught the attention of scholars again. The reason for this was because social disorganization theory focused on ecological units such as neighborhoods and cities instead of on individual people.

The first researchers to revamp social disorganization theory were Judith and Peter Blau. They studied the 125 largest metropolitan areas in the United States and hypothesized that "variations in rates of urban criminal violence largely result from differences in racial inequality in socioeconomic conditions" (Blau & Blau, 1981, p. 114). They confirmed what Shaw and McKay drew up in their original theory by showing that violence generally increased in areas marked by economic inequality and racial inequality. After this initial study was done, research with social disorganization theory expanded and took on a new light.

After this revamp of social disorganization theory, many researchers continued to ask questions of why crime was being committed in certain neighborhoods. There have been many studies done in the United States and abroad to test social disorganization theory. In the United States, researchers have studied many different types of communities ranging from metropolitan areas to rural areas. For metropolitan areas, it has been found that there were higher rates of violent crime in neighborhoods that were racially mixed (Kingston, Huizinga, & Elliot, 2009). Also in these racially mixed communities, there were lower levels of social control and smaller social networks, which meant that residents were less likely to intervene on behalf of the common good of the neighborhood. From this they were also able to conclude that residents from poorer neighborhoods perceived less effective social institutions such as educational, recreational, and health needs of residents, which led to higher rates of violent offending.

For nonmetropolitan areas, support has not been found for social disorganization theory. Kaylen and Pridemore's (2013) study on rural violence found that the way that the dependent variable (juvenile delinquency) was measured would be a determining factor on whether social disorganization theory was supported or not. Instead of utilizing county-level UCR arrest data, they used victimization data from hospitals and emergency rooms. They believed that county-level UCR arrest data would be problematic because smaller counties and rural cities may not report in the same way that bigger, urbanized cities were reporting their crime statistics. The problem with smaller, rural counties deals with non-reporting and undercounting of arrests. This problem was solved by using hospital victimization data. When initially looking at previous studies, they found that social disorganization theory was generalized to rural communities and this proved problematic. Their ultimate conclusion was that social disorganization theory might only apply to urban areas and not rural areas. They concluded that the three factors of social disorganization theory did not apply to rural areas as it did with urban areas because family factors played a bigger role than ethnic heterogeneity, socioeconomic status, and residential mobility. Specifically with socioeconomic status, those families that were in poverty may not face the same challenges as those in urban settings. Many families who lost jobs or houses would not move out of the county instead find another place within the county to live. .

When comparing metropolitan and nonmetropolitan areas, it has been found that crime has generally been lower in nonmetropolitan areas. Crime in nonmetropolitan counties showed to be about one-half the averages when compared to metropolitan counties. This was due to greater social interactions in smaller communities (Barnett and Mencken, 2002). They found that with population stabilization, communities that had lower rates of property crime were ones that were closely knit and looked out for each other's property. For violent crime, this was not the case. Violent crimes involve intimate relationships and, when paired with low socioeconomic status, greater amounts of violent crime were committed because of resource disadvantage. Even with population stabilization, this was not enough to stop people from being violent.

In the United Stated and Europe, many studies have been done and there seems to be support for social disorganization theory. This shows that not only can this theory be related to the culture in the United States but can be applied to different cultures and countries as long as the three exogenous variables for social disorganization theory were present.

The first study to test this was Sampson and Groves in 1989. They looked at 238 parliamentary constituencies in Great Britain from a 1982 national survey and 300 parliamentary constituencies in Great Britain from a 1984 survey. In Great Britain, parliamentary constituencies are the equivalent of neighborhoods in the United States. They found that communities with sparse friendship networks, unsupervised teenage peer groups, and low organizational participation had higher rates of crime and delinquency. This was due to the effects of community structural characteristics such as low socioeconomic status, residential mobility, and ethnic heterogeneity. While they did try to explain all the factors of social disorganization theory, they did note that not all factors were measured thoroughly. With some of these factors, the researchers were not fully able to measure it because the data they were using was not an exhaustive list of what the variable actually meant. Because of this they were not able to definitively conclude that all of the dimensions of community organization were correlated to why crime and delinquency occurred.

To follow up on Sampson and Groves' study, Veysey and Messner (1999) used advanced technology that was not available to Sampson and Groves to fully test whether their conclusions were correct. Partial support was found for Sampson and Groves' study. They found that the measures of social disorganization did not measure the same dimensions as the original study intended to measure, meaning that, instead of trying to measure one underlying factor, they found that it measured multiple underlying factors. Also Veysey and Messner concluded that each of the three variables Sampson and Groves tested was only measured by a single-item indicator.

One criticism of Shaw and McKay's theory was that it "paints too rosy a picture of communities outside the inner city" (Cullen & Agnew, 2010, p. 98). Although Shaw and McKay focused mainly on delinquency in the inner city, their research did not address that delinquency also happens in communities outside of the inner city. It was the makeup of the community that contributed to crime being committed. Also social disorganization does not fully explain why delinquency was committed; it just shows what community factors may contribute to crime being committed in certain areas. Shaw and McKay explored all of the dimensions of disorganization and how each one was criminogenic but did not explain how all of these factors create higher rates of delinquency (Bursik & Grasmick, 1993). Even if the factors and variables were being measured correctly, many studies noted that not all of the factors and variables that were trying to be measured were being measured to the fullest extent. Many were only proxy measures and this could prove to be problematic when trying to analyze the data.

For all of the studies mentioned so far, there were many different ways in which independent variables were measured. Although it is not an exhaustive list, Table 1 lists and describes the most commonly used independent variables.

Table 1: Previous Studies Independent Variables		
Theory Variables	**Independent Variables**	**Description of Variables**
Ethnic Heterogeneity	Ethnicity/Race	Index created based on people living in the community or percent nonwhite
Economic Status	Poverty	Percent of people living below the poverty line
	Single Family Households	Percent of single parent head of households or female head of households
Residential Mobility	Residential Stability	People who lived in a different household in the last 5 years or people who grew up within a 15 minute walk of where they currently live

Spatial Analysis

With spatial analysis, there are many different techniques that can be used to find out if there are correlations in space. The technique that is often used is exploratory spatial data analysis (ESDA) which reviews the spatial distribution of events or incidences at the global level with the use of Moran's I, then reviews the spatial distribution patters at the local level using local indicators of spatial association (LISA). Global level indicators "summarize the overall pattern of dependence in the data into a single indicator" (Getis & Ord, 1992, p. 200). Local level analysis enables researchers to "detect pockets of spatial association that may not be evident when using global statistics" (Ord & Getis, 1995, p. 288). From these maps, positive or negative spatial autocorrelation can be detected and the identified spatial distribution patterns can be formed through spatial regression models. Spatial autocorrelation tells us about the coincidence of similarity in value with similarity in location. It "tells us about the interrelatedness of phenomena across space, one attribute at a time. It deals simultaneously with similarities in the location of spatial objects and their attributes" (Longley, Goodchild, Maguire, & Rhind, 2011). When features were similar in location and in attributes then it would be considered positively spatially autocorrelated. When features were dissimilar in location and in attributes then it would be considered negatively spatially autocorrelated. When attributes were independent of location they were considered to have zero autocorrelation.

To extend upon spatial autocorrelation, researchers used exploratory spatial data analysis to find patterns in the data they were working with. Before going into detail about ESDA, we first have to look at the history of this technique. ESDA was an extension of the traditional exploratory data analysis or EDA. John Tukey developed EDA in 1977 and it was used to "identify data properties for the purposes of pattern detection in data, hypothesis formulation from data, and for some aspects of model assessment such as goodness to fit" (Tukey, 1977). Based on EDA, ESDA was formed so that spatial patterns could be analyzed. It was an upgraded version of EDA that allows users to use additional techniques to assess spatial models (Haining, 1993). ESDA was defined as "a collection of techniques to describe and visualize spatial distributions; identify atypical locations or spatial outliers; discover patterns of spatial association, clusters, or hot spots; and suggest spatial regimes or other forms of spatial heterogeneity" (Anselin, Cohen, Cook, Gorr, & Tita, 2000). Spatial heterogeneity was the "changing structure or changing association across space" (Longley et.al, 2011).

The use of ESDA has been around since the 1990s and has been used on various levels of crime data including point data (knowing where the specific crime occurred) and areal data (crime rates in a county) (Anselin et. al, 2000). With advancements in technology, mapping where crime was occurring has become easier and more practical. There were numerous types of programs that will allow users to input their data to transform it into a map so that it can be analyzed.

Anselin has done the most research in the area of ESDA specifically when dealing with spatial econometrics and regional science. It was no surprise that he has also looked at other disciplines especially criminal justice to see if results would transfer across the disciplines. Messner, Anselin, Baller, Hawkins, Deane, and Tolnay (1999), wanted to find out if homicides could spread from one geographical area to another, specifically in counties in and around St. Louis, MO. By using ESDA, they were able to find that homicides were not randomly distributed throughout the St. Louis area. Interestingly enough, they found that communities that were affluent or rural/agricultural acted as a barrier to the spread of homicide.

To follow up on their previous study Baller, Anselin, Messner, Deane, and Hawkins (2001) studied homicide rates again but this time instead of using two time periods (one marked by stable homicide rates and one marked by increasing homicide rates), they looked at the decennial years between 1960 and 1990 at the county level. Based on previous research, they hypothesized that "county-level homicide rates will exhibit statistically significant and positive spatial autocorrelation" (p. 563). Results showed that when looking at the global level, all years were statistically significant which meant that there was strong evidence of a significant spatial pattern. At the local level, they found that clustering of high homicide rates was mostly in the South while clustering of low rates was found in the Northeast, Midwest, and West. From their OLS regression results, they found that counties with younger populations have higher homicide rates, counties with higher unemployment have lower homicide rates because of less opportunity to socialize, and resource deprivation, population structure, divorce, and Southern location were positively related to higher homicide rates.

Not only has ESDA been used in the United States to test crime distributions but also it has been used in other countries for crime analysis. In Australia, researchers used GIS and spatial analysis approaches for examining crime occurrence in suburbs. With exploratory spatial data analysis, they were able to cluster all of their data to conclude relationships in the spatial distribution of crime and from the corresponding Moran's I, they were able to indicate that there should be positive spatial autocorrelation with property crime at the global level. At the local level, using local indicators of spatial association, they confirmed that there was a positive spatial autocorrelation in the city center based on the surrounding suburbs. From the multivariate regression results, they found four significant spatial variables in relation to property crime per 1,000 residents; density of public transport stops in suburbs, and distance to closest police station, ferry platform, and Brisbane River (Murray, McGuffog, Western, and Mullins, 2001).

ESDA was not limited to only looking at crime patterns; it could be used to look at any spatial patterns. For example in the UK (Tan & Haining, 2009), ESDA was used to look at health and quality of life outcomes when crime was present in the city of Sheffield. By looking at other outcomes other than crime this can help to create better policies that will target agencies that can help one another. Another example of this was looking at the prevalence of alcohol and drugs in a community at the census block level and where these can be obtained (Banerjee, LaScala, Gruenewald, Freisthler, Treno, and Remer, 2008).

Social Disorganization and Spatial Analysis

Research on social disorganization theory and spatial analysis has been going on since the 1940s when Shaw and McKay originally plotted where juvenile offenders lived. With the advancements in technology, we have moved from plotting points on a map to uploading the points into a computer program and having the program give us the results. It has become easier to obtain definitive answers through technology because we were no longer guessing as to what was significant and what was not.

There were numerous studies that use different levels of data. Some researchers feel that county-level data accurately capture what they were trying to measure while other researchers felt that it was too broad and did not capture all of the processes, so instead used census blocks, census tracts, neighborhoods, or cities. When looking at original data for social disorganization theory, neighborhood level data was used. As with any study, there were pros and cons for determining what level of data to use while also determining what type of data will capture all of the proposed measures.

Many studies used census tract level data when looking at social disorganization theory because this theory originally dealt with neighborhood level data. There were mixed results in support for social disorganization theory. For those who did find support for social disorganization theory, all of the initial factors were not always significant. Law and Quick (2013) studied the York Region of Southern Ontario from January 1, 2006 to December 31, 2007 at the census dissemination areas. They used non-spatial and spatial models to identify significant variable related to young offender locations. From the non-spatial model, they were able to conclude that seven variables were significant: unemployment, immigration, ethnic heterogeneity, aboriginals, residential mobility, dwellings constructed before 1946, and government transfer payments. From the spatial model, they found that out of the seven variables that were significant from the non-spatial model only three remained significant: residential mobility, government transfer payments, and ethnic heterogeneity. When looking at the variable of government transfer payments, it could be a measure for poverty but it does not capture the whole concept of poverty. From this we can see that only two out of the three variables stated by Shaw and McKay were significant.

Even though this previous study looked at all juvenile delinquency, there were other studies that have looked at specific crimes. For example, Suresh, Mustaine, Tewksbury, and Higgins (2010) looked at registered sex offenders in Chicago neighborhoods at the census tract level. Although this does not tie directly into juvenile delinquency, it was still interesting to see the results of this study and how it could be translated to adult crimes. Their results showed that there were high clusters of lower median housing income, community poverty, unemployment, and vacant housing where these registered sex offenders were living. These places were smaller geographical areas and almost all of the registered sex offenders tended to live in these specific places. When looking at other affluent neighborhoods, there were either very few registered sex offenders or none at all.

Continuing with specific crimes for adults, results have shown significance in other countries. Canada has a lower crime rate than the United States, though similar to the US in terms of industrialization. For this particular study, Andresen (2006) not only analyzed his data against social disorganization theory but also analyzed it against routine activity theory at the census tract level. He wanted to study both of these theories because he was following previous research that has combined theories to make them stronger. He found that high unemployment and the presence of young populations were the strongest predictors of criminal behavior. By using both of these theories together, he was able to piece together what aspects will ultimately be predictors for criminal behavior. By just using one theory, he was limiting himself to only those variables that were defined within the specific theory.

Researchers who did not find support for social disorganization theory found that the results of their study were better explained by other theories or that the variables they were trying to measure were not significant. The variables may not be significant because they were being measured in the wrong way and do not fully capture what the entire variable was supposed to measure.

Although Andresen has found partial support for social disorganization theory, he has also done a study where he has found no support whatsoever. In his 2006 study again studied social disorganization theory and routine activity theory but this time used ambient and residential populations. Specific crimes he looked at were automotive theft, break and enter, and violent crime. Strong support was found for routine activity theory across space and the use of ambient populations when calculating crime rates and measuring the population at risk. Social disorganization theory did not provide any statistically significant results for residential or ambient populations. Although the variables for social disorganization were significant, they could be better explained with routine activity theory.

Another study that looked at a specific crime being committed was done by Morenoff, Sampson, and Raudenbush (2001). They looked at structural characteristics from the 1990 census and survey responses from Chicago residents in 1995 to study the homicide variations in following years at the census tract level. Using ESDA, they found that homicide events were not randomly distributed throughout the city and that there was a high degree of overlap between the spatial distributions of collective efficacy and homicide. Neighborhoods that were high in collective efficacy made up for 72% of the low clusters of homicides whereas neighborhoods that were low in collective efficacy made up for 75% of the high clusters of homicides. From the multivariate analysis, they found that concentrated disadvantage, collective efficacy, and the index of concentration at the extremes were related to homicide through all models of the study. They found that the spatial proximity to violence, collective efficacy, and alternative measures of neighborhood inequality were predictors of variations in homicide. Race did not play a factor in the result of higher homicide rates based on structural characteristics and social processes having similar effects on homicide rates. From this they concluded that although there was some support for social disorganization theory, local organizations, voluntary associations, and friendship networks only promoted collective efficacy. Collective efficacy helped residents in achieving social control and cohesion but beyond that it did not stop homicides from happening.

CHAPTER 3

THE CURRENT STUDY

Research Questions and Hypotheses

This proposed study will examine the following questions: 1) Were there certain areas of the U.S. that had higher concentrations of violent crime rates and/or property crime rates? What was the spatial neighboring county effect of crime rates in the identified local clusters (LISA)? 2) Has there been a shift of violent and/or property crime rates over the three different time periods? 3) Do any of these results change when comparing adults and juveniles? 4) Based on the three exogenous variables of social disorganization theory (ethnic heterogeneity, socioeconomic status, and residential mobility), is there support for this theory for adults and juveniles? and 5) Were crime rates concentrated in the MSA counties at the local level?

By asking these research questions, this study hypothesizes that 1) based on previous research, violent crime rates should be higher along the coastlines of the United States while property crime rates should be higher in the Midwest. From the identified local clusters (LISA), the unobserved behaviors of neighboring counties can be looked at to see the effect on the subject county's crime rates. The areas that have clusters of high crime rates should decrease while the areas that have clusters of low crimes rates should increase. 2) Since crime has been decreasing over the years, this paper hopes to conclude that violent crime rates and property crime rates continue the trend of declining. By analyzing the spatial distribution of crime, there should be less concentrations of crime being committed in certain areas, specifically along the coastlines with violent crime rates and in the Midwest with property crime rates. 3) When comparing adults and juveniles, the pattern of crime rates should be the same. With the declining trend of crime rates, it should not matter if it is for adults or juveniles, both should be declining over the years. Also the same pattern should be seen in the identified local clusters as well as where violent crime rates and property crimes are concentrated. 4) Based on previous research, the theory should be partially supported. There might be greater support for social disorganization theory when looking at adults because adults commit a greater proportion of crimes than juveniles do. Juveniles make up a small sample of all crimes committed and not all agencies collect complete crime data on juveniles that were in the system. This may show that there may not be a big enough sample in order to fully test social disorganization theory and complete a full spatial analysis. Also because crime rates are being analyzed at the county level, the theory may not be supported because it was originally intended to be measured at the neighborhood level. This could prove to be problematic when trying to draw conclusions because of the unit of analysis is not the same as the theory intended. 5) Crime rates will be higher in the MSA counties when compared to non-MSA counties because of the urbanization of cities. MSA counties have higher overall populations which would contribute to overall higher violent crime rates and property crime rates when compared to non-MSA counties.

Data Sources and Sample

To examine how different socioeconomic factors will affect crime in the United States, this study will incorporate data from the American Community Survey (ACS), Bureau of Labor Statistics (BLS), Census, Bureau of Economic Analysis (BEA), Internal Revenue Service (IRS), and National Archive of Criminal Justice Data. Data for all of the contiguous United States counties including Washington D.C. will be collected which will give a study area of 2,868 counties for the decennial census of 1990, 2000, and 2010. Since Hawaii and Alaska were geographically separated from the continental United States, they will not be included for analysis. Also, data was missing for Florida, Illinois, and Wisconsin in different years so they will not be included for analysis. County level data will be used for this study because there has not been a lot of research conducted at the county level when testing against social disorganization theory. This may be because Shaw and McKay originally tested their theory at the neighborhood level. Also, the availability of data was able to be obtained easier than if trying to obtain data at the census tract level.

Variables and Measures

Table 2: Dependent Variables	
Violent Crimes	Murder
	Rape
	Aggravated Assault
	Robbery
Property Crimes	Burglary
	Larceny
	Motor Vehicle Theft
	Arson

The total number of violent and property crimes for adults and juveniles will be analyzed as seen in Table 2. In addition, the overall total number of crime will be measured which will include all Part 1 crimes as defined by the FBI. To standardize these crime variables, the total number of crimes will be divided by the population size of the county then multiplied by 100,000 in order to get the number of crimes per 100,000 population or the standardized crime rates.

Independent Variables for this study will include the unemployment rate, median household income, race (White, Black, Hispanic, American Indian, Asian, and Two or More Races), all poverty (share of the total population in poverty), family poverty (share of families in poverty), education (no high school diploma, high school diploma or equivalent, some college completed, associate degree, bachelor degree, and graduate degree or higher), household status (married families, male head of households, and female head of households), residential mobility (share of population that has moved in and out of a county), and a urban-rural dummy variable (MSA or non-MSA).

Pearson's correlation showed that some of the independent variables were highly correlated and measured the same concept so accurate results would not be obtained if all independent variables were used. Because of these correlations, some variables were not used in the spatial regression model and dropped from the study. For example, the variables of 'income', 'unemployment', 'family poverty', and 'all poverty' have very high correlations to each other. In order to narrow down which independent variables will measure the dataset the best, all of the other independent variables had to be looked at for correlations. Based on Pearson's correlation and the results of the spatial regression model, two independent variables were chosen for each of the three overall variables for social disorganization theory. Table 3 lists and describes the independent variables that were used in this study along with their expected sign.

Table 3: Independent Variables			
Theory Variables	**Independent Variables**	**Description of Variables**	**Expected Sign**
Ethnic Heterogeneity	Black	Share of the population who was Black	+
	Hispanic	Share of the population who was Hispanic	+
Economic Status	All Poverty	Share of the total population considered to be in poverty as indicated by the current poverty level	+
	No High School Diploma	Share of the total population over 25 who did not complete high school or its equivalent	+
Residential Mobility	Migration Inflow	Share of population that has moved into a county in a given year	+
	Migration Outflow	Share of population that has moved out of a county in a given year	+

Metropolitan Statistical Areas were defined as "geographic entities delineated by the Office of Management and Budget (OMB) for use by Federal statistical agencies in collecting, tabulating, and publishing Federal statistics" (Census, 2013). A metro area was defined as having a core population of 50,000 or more and can include more than one county. A micro area was defined as having a core population of 10,000 or more and can include more than one county. Every ten years all areas were reviewed and revised to see if they meet the standards to be called a metropolitan statistical area.

Analytical Techniques

Using ArcGIS[1], a shapefile was created based on all counties from the contiguous United States. A raw shapefile of the United States at the county level was obtained from the TIGER/Line files (Topologically Integrated Geographic Encoding and Referencing) of the Census Bureau. A secondary data containing all of the variables was joined to the

[1] ArcGIS was a geographic information system that allows a user to work with data that was tied to a particular location on the earth. It can create, share, and manage geographic data, maps, and analytical models using desktop and server applications.

shapefile to create a master file. Using GeoDa[2], maps were created to look at the global distribution of crime to see if there were any distinctive patterns of spatial distribution. The first step in our analysis was using exploratory spatial data analysis or ESDA. This was an extension of exploratory data analysis (EDA) to detect spatial properties of data sets. It was an inductive approach that enables us to establish a hypothesis by discovering existing spatial pattern of our study region. In order to find out if there were spatial effects we use a spatial weights matrix, which quantifies the spatial relationships that exist among the spatial units (county) in the dataset. Based on the spatial structure from the spatial weights matrix, we employ two largely used techniques in ESDA to detect spatial autocorrelation. The first technique was the Global Spatial Model, which measures the overall spatial clustering of the data. In order to detect global spatial autocorrelation we use the Moran's I statistic (Equation 1).

1)

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w(i,j)} \left[\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w(i,j)(xi-\bar{x})(xj-\bar{x})}{\sum (xi-\bar{x})^2} \right]$$

where, N= the number of spatial units indexed by *i* and *j*

x= the variable of interest

x bar=s the mean of x

w_{ij}= an element of a matrix of spatial weights

The first set of maps made was to look at the spatial distribution was using a box map at the 1.5 hinge. This type of map shows the difference between the 25% and 75% value and was designed to show quartile distributions with outliers defined by upper and

[2] GeoDa was developed by Dr. Luc Anselin and was designed to implement techniques for exploratory spatial data analysis (ESDA) on lattice data (points and polygons).

lower hinges (Maps 1-18). The second technique was the Local Spatial Model to evaluate the clustering in those individual units by calculating Local Moran's I (Equation 2) for each spatial unit and evaluating the statistical significance which was also known as the Local Indicators of Spatial Association or LISA (Anselin, 2005).

2) The local Moran statistic for areal unit *i* was:

$$I_i = z_i \sum_j w_{ij} z_j$$

where, z_i= the original variable x_i in "standardized form" $z_i = \frac{x_i - \bar{x}}{SD_x}$

w_{ij} = the spatial weight

The summation, $\sum_j$ was across each <u>row</u> *i* of the spatial weights matrix

The second set of maps made was to look at the local spatial distribution using a univariate local Moran's I. This computes a measure of spatial association with the neighbors for each individual location. There were five main colors that were used in a LISA map. Blue indicates a 'low-low' cluster meaning that a subject county has low crime rates and was surrounded by its neighbor counties with low crime rates. Violet indicates a 'low-high' cluster meaning that a subject county has low crime rates and was surrounded by it neighbor counties with high crime rates. Red indicates a 'high-high' cluster meaning that a subject county has high crime rates and was surrounded by its neighbor counties with high crime rates. Pink indicates a 'high-low' cluster meaning that a subject county has high crime rates and was surrounded by its neighbor counties with low crime rates. Grey indicates that a county was not significant based on a pseudo significant level of 0.01. The 'high-high' and 'low-low' locations were considered spatial clusters while the 'high-low' and 'low-high' locations were considered spatial outliers

(Anselin, 2005). Based on results from the Local Spatial Model, the thirty counties that have the highest violent and/or property crime rate will be analyzed further by first order, second order, and third order counties based on queen contiguity. Queen contiguity was a method to determine neighborhood structure by counting the counties sharing either a common border or vertex with the subject county as neighborhood counties of the subject county. This technique will be used to identify distinctive spatial distribution patterns with potential spatial clusters as articulated in the first research question.

Since this was a dynamic study using three distinct time periods, the first step will be to compare adults and juveniles for each specific year against one another. This will allow us to see individual difference between adults and juveniles for each specific year. The next step will be to compare the results from the different decennial years for adults against each other and the results from the different decennial years for juveniles against each other. This will allow us to see the temporal difference in crime rates for adults and for juveniles individually. The last step will be to compare all three years for adults and compare them to the three years for juveniles. This will allow us to see the overall temporal difference in crime rates between adults and juveniles. This analysis process was designed to detect overall spatial distribution patterns at the global level and local spatial clusters and outliers at the local level.

After detecting spatial distribution patterns, spatial regression models were specified to estimate the effect of socioeconomic factors in crimes rates using GeoDa. The first step was to perform the Lagrange Multiplier test with OLS models to find out which statistical model will fit best and to find the spatial effects of different socioeconomic variables. Based on the results of the Lagrange Multiplier test, the relevant models that can be determined were either Robust LM lag model or the Robust LM error model with spatial effects. This analysis process was designed to detect the changes in the role of socioeconomic factors to explain crime rates over the given decennial years between adults and juveniles. By using a spatial regression model, it expands upon the standard liner regression model of Ordinary Least Squares because it shows the spatial dependence in the variables.

Along with the variables that were associated with Social Disorganization Theory, a set of urban-rural dummy variables will be included in the spatial regression model estimation to find out if crime rates were concentrated in counties classified as MSA (urban) counties or if crime rates were concentrated in counties classified as non-MSA (rural) counties. This analysis process was designed to detect whether crime rates were concentrated in MSA or non-MSA counties.

CHAPTER 4

RESULTS

Results of Exploratory Spatial Data Analysis (Global Level)

By using spatial distribution maps, the overall clustering of crime rates in the United States are able to be seen. These results will show the comparison for three discrete study periods (1990-2000-2010) for adults and juveniles and also the temporal shift over the years. Not only were the spatial distribution maps being analyzed but also the Moran's I for each of the cases was being analyzed. The Moran's I values show if spatial autocorrelation was present.

In order to properly compare the Moran's I across years and different types of crimes, the values have to be standardized as seen in Equation 3. The way this was done was by taking the Moran's I value subtracting the mean from the Moran's I value then dividing it by the standard deviation.

3) $$z = \frac{y-\bar{x}}{\sigma}$$

where z= the standardized Moran's I value

y=Moran's I value

x bar=the mean

σ =the standard deviation

Based on Table 4 we can see that there was tendency toward clustering because all values were positive and this shows that there was positive global spatial autocorrelation. This means that the spatial distribution of crime was not random and there were clusters in the given dataset.

Table 4: Standardized Moran's I						
	All Crime Adult	All Crime Juvenile	Violent Crime Adult	Violent Crime Juvenile	Property Crime Adult	Property Crime Juvenile
1990	16.5***	17.5***	20.3***	12.4***	12.2***	16.2***
2000	22.8***	20.3***	36.0***	19.7***	24.5***	14.8***
2010	17.5***	18.4***	34.1***	19.6***	24.5***	13.7***
*Pseudo-P ≤ 0.05 ** Pseudo-P ≤ 0.01 *** Pseudo-P ≤ 0.001						

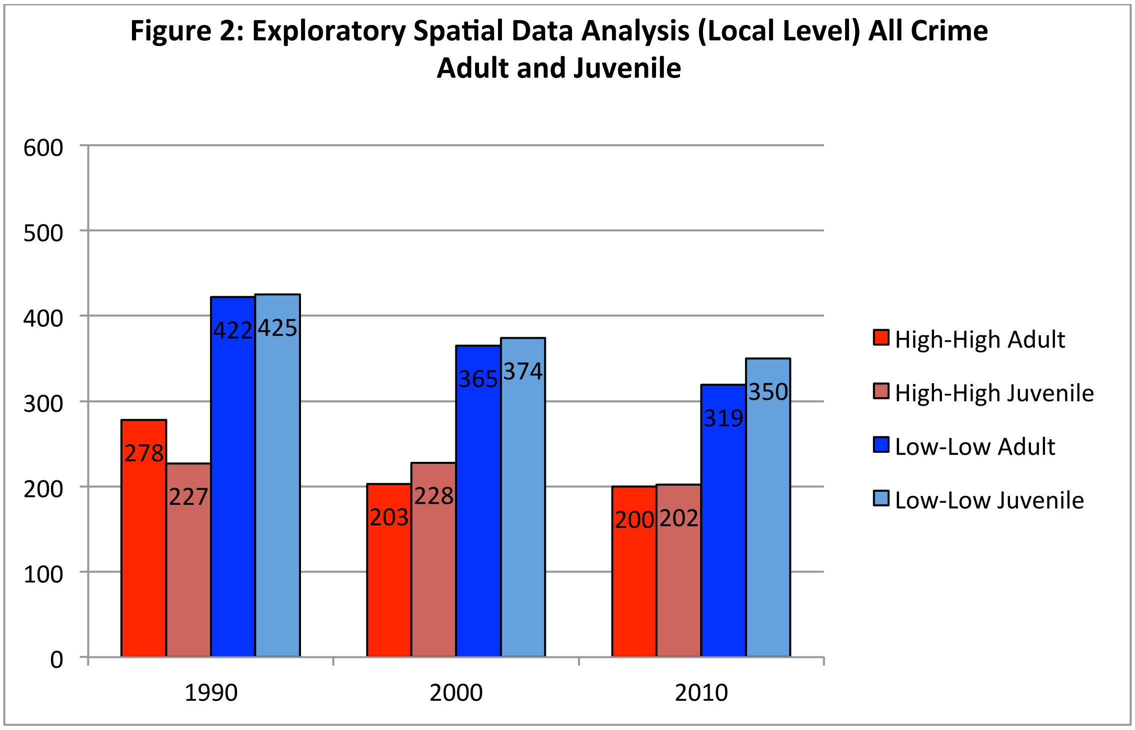
Results show that there was an increase in the standardized Moran's I values in the years between 1990 and 2000 for all crime types except for juvenile property crime (reduced to 14.8 from 16.2 in 1990) but then the standardized Moran's I values slightly decline in the years between 2000 and 2010. The values in the years between 2000 and 2010 do not decrease as intensely as the given values did when they were increasing between the years of 1990 and 2000. The decreasing rate between years 2000 and 2010 was not as fast as the increasing rate between the years 1990 and 2000. The highest overall global spatial autocorrelation was in the years between 1990 and 2000 with adult violent crime at 36.0.

When looking at the standardized Moran's I values for adult violent crime, there was a stronger positive spatial autocorrelation for all years compared to adult property crime for all study years. This was untrue for juvenile crime. Unlike 1990, the global spatial autocorrelation was stronger for 2000 and 2010 when comparing juvenile violent crime to juvenile property crime but for 1990 it was the opposite. There was stronger positive spatial autocorrelation for juvenile property crime than for juvenile violent crime. Juvenile property crime shows that the spatial autocorrelation steadily declines over time since 1990. This means that the greater the positive standardized Moran's I value, the more the data will tend to be clustered versus if the standardized Moran's I values were negative then the data will tend to be dispersed. When the data tends to be clustered then the features are similar in location and in attributes. Overall, the greatest amount of clusters is in 2000.

From these standardized Moran' I values we can see that there was statistically significant positive spatial autocorrelation for all given years. The Moran's I values were not independent of each other, so we were able to move on to the next step of the spatial analysis by using the local level exploratory spatial data analysis to find out where the specific clusters were located. This process will show how each county influences a neighboring county in the spatial distribution of crime.

Results of Exploratory Spatial Data Analysis (Local Level)

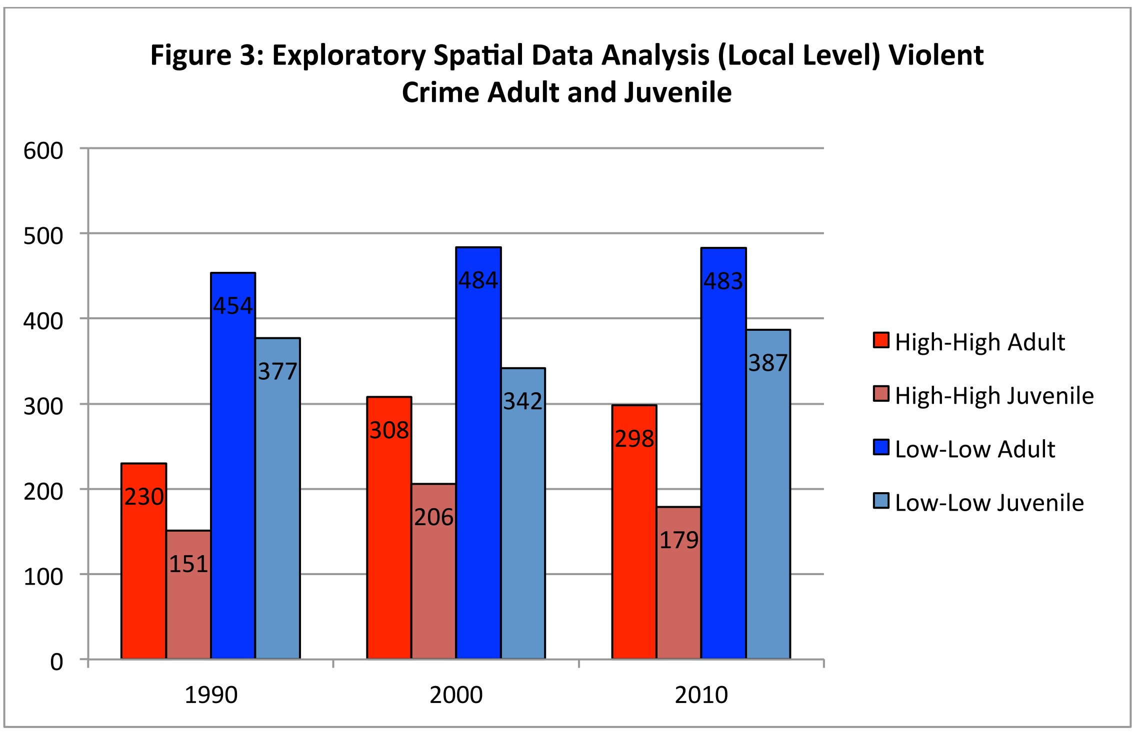
By analyzing the data at a local level, we were able to see the individual effect that one county has on a neighboring county. These maps will show the spatial clusters of high/low crime rates surrounded by neighboring counties with high/low crime rates and the spatial outliers of low/high crime rates surrounded by neighboring counties with high/low crime rates. Below are the figures for the number of counties for each crime type over the study period. It must be noted that all counties were not included in the figures because those counties were not significant at the 0.01 level. The figures do not depict the spatial outliers since the main focus will be on the main spatial clusters of 'high-high' and 'low-low'. Overall, it can be shown that there were a greater number of counties classified as 'low-low' cluster when compared to those counties classified as 'high-high' clusters for all crimes and all years. There are a greater number of counties classified as 'low-low' clusters because of the continuing decline in the national trend.



For "All Adult Crime", there was a decline in the number of significant counties overtime for 'high-high' and 'low-low' counties (Figure 2). For "All Juvenile Crime", there was a decline in the number of 'low-low' counties overtime while there was an increase of one county between the years 1990 and 2000 for the 'high-high' clustering with a decrease between the years 2000 and 2010.

When looking at the corresponding maps (Map 19-21) for "All Adult Crime", the 'high-high' spatial clustering was located in California, Texas, and the East Coast in 1990. As time passes these 'high-high' clusters have shifted to the East and a 'high-high' cluster has formed in the Northeast. Consistently, there was a 'high-high' cluster in Northern California. The 'low-low' spatial clustering was located in the North, Midwest, and parts of the South. There were smaller 'low-low' spatial clusters in the Northeast while there were none on the West Coast. The Midwest consistently shows 'low-low' clusters of crime rates. The 'low-low' clusters in the South in the 1990s have changed into 'high-high' clusters in 2000 and were observed again in 2010.

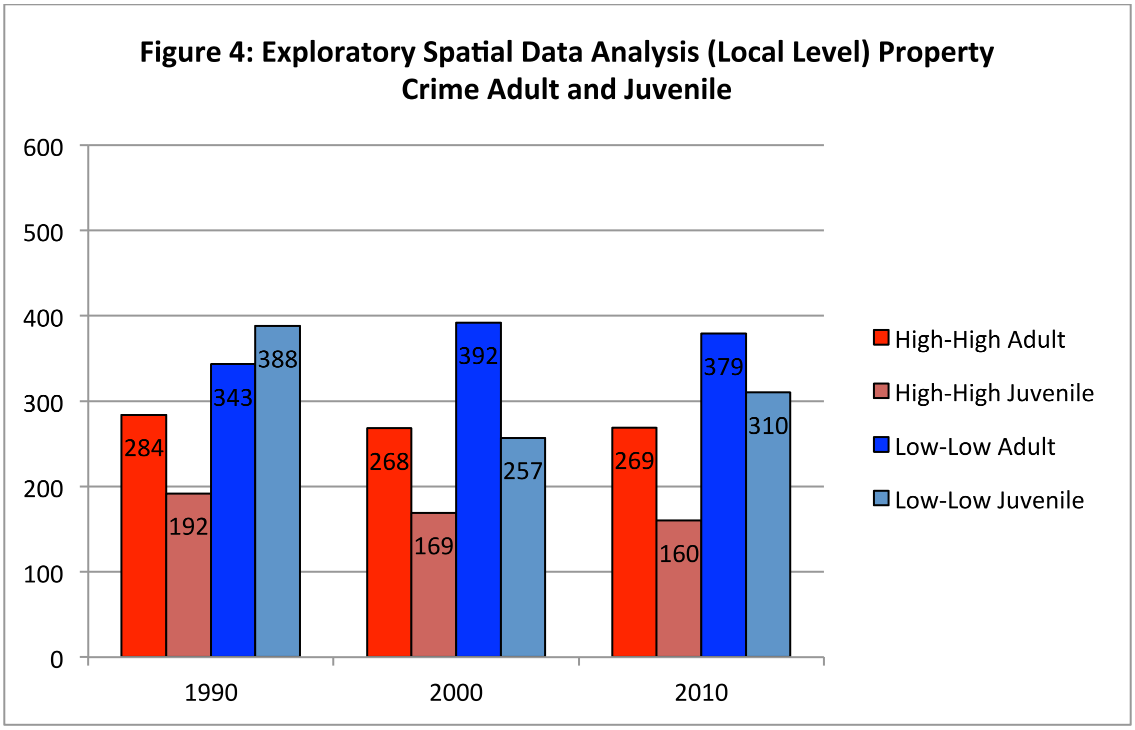
When looking at the maps (Map 22-24) for "All Juvenile Crime", there were 'high-high' clusters in the West, Texas, Minnesota, and New York area. This was consistent over time although these 'high-high' clusters decrease in size over time. Looking at the South and moving East shows that there were consistently 'low-low' clusters but these clusters become more defined in specific areas overtime, such as Georgia, Kentucky, and West Virginia, and were not spread out across a given area. There were smaller 'low-low' clusters spread throughout the Midwest.



For "Adult Violent Crime" (Figure 3), for the main spatial clustering there was an increase between the years 1990 and 2000 and a decrease between the years 2000 and 2010 for both 'high-high' and 'low-low' clusters. For "Juvenile Violent Crime", the main spatial clustering for 'high-high' increases between the years 1990 and 2000 and decrease between the years 2000 and 2010 and this was the opposite for ‘low-low’. The main spatial clustering for ‘low-low’ clusters decrease between the years 1990 and 2000 and increase between the years 2000 and 2010.

For “Adult Violent Crime” (Maps 25-27), California, and its surrounding states, and the East Coast have the greatest number of ‘high-high’ clusters for all years. The ‘high-high’ clusters in the surrounding states in California show a steady decline over the years but the clusters in the East Coast show an increase in 2000 with a decrease in 2010. The South also shows ‘high-high’ clusters that increase in 2000, specifically around Louisiana, but spread out in 2010. ‘Low-low’ clusters were concentrated in the North, Midwest, and Northeast for all years with ‘low-low’ clusters increasing in size in Utah and parts of Texas but decreasing in size in the Midwest and North.

Juvenile violent crime rates almost mirror that of adult violent crime rates (Maps 28-30). California and the East Coast have ‘high-high’ clusters for all years. The clusters in these areas increase over time with the addition of Louisiana in 2000. There were smaller ‘high-high’ clusters in Utah, Washington, and Texas, and Arizona in any given year and these clusters decrease over time. The ‘low-low’ clusters were concentrated in the Midwest with the size of the clusters becoming more concentrated in a specific area over time and smaller ‘low-low’ clusters in the Northeast.



For "Adult Property Crime" (Figure 4), the main spatial clustering for 'high-high' decreases between the years 1990 and 2000 and remains steady through 2010. For the main spatial clustering for 'low-low' there was an increase between the years 1990 and 2000 and a decrease between the years 2000 and 2010. For "Juvenile Property Crime", there was a steady decline in the 'high-high' main spatial clustering over time. For the 'low-low' clusters, there was a dramatic decrease between the years 1990 and 2000 with the number of counties increasing between the years 2000 and 2010.

"Adult Property Crime" (Maps 31-33) shows that there were 'high-high' clusters along the West Coast into Arizona in 1990 but when looking to later years, the 'high-high' clusters were only in Washington and Oregon and nonexistent along the coast by 2010. The 'high-high' clusters in Texas have also reduced and have become 'low-low' clusters by 2010. There were 'high-high' clusters increasing in the South and along the East Coast that have increased in size overtime. The Midwest shows the greatest concentration of ‘low-low’ clusters with smaller ‘low-low’ clusters in the Northeast that decrease as the years pass.

“Juvenile Property Crime” (Maps 34-36) results show that ‘high-high’ clusters were mainly in Washington, Oregon, Utah, and Arizona. These clusters decrease over time but were present throughout all years. In California, there were ‘high-high’ clusters but they decrease in size over time. Over time the ‘high-high’ clusters in New Jersey and Pennsylvania decrease in size with the ‘high-high’ clusters increasing along the East Coast and Louisiana. The ‘low-low’ clusters were concentrated in Georgia and states surrounding Kentucky and West Virginia. The ‘low-low’ clusters in Georgia decrease over time but the ‘low-low’ clusters surrounding Kentucky and West Virginia increase over time. These were also ‘low-low’ clusters that increase in size in the Midwest.

From this analysis, it can be concluded that there is a decline in the number of ‘high-high’ spatial clustering and an increase in the number of ‘low-low’ spatial clustering. This is important because it confirms what previous research has stated about the decline in the number of crimes being committed in the United States. Also with the corresponding maps, results do not confirm what previous research has stated. Previous research has stated that violent crime rates would be higher along the coastlines while property crime rates would be higher in the Midwest. This is partially supported. Violent crime rates tended to be on the coastlines for any given year but ‘high-high’ spatial clusters along the West Coast decrease while the ‘high-high’ spatial clusters along the East Coast increase. For property crime, the Midwest shows that lowest amount of crime rates while the highest crime rates are along the coastlines.

Results of Spatial Regression Models

For spatial regression model specification, the first step was to find out the fit of the model that will work for a certain set of variables. In order to do this the Lagrange Multiplier lag and Lagrange Multiplier error was looked at. If both of these values were significant then the corresponding Robust LM lag or Robust LM error was looked at. Whichever one of these values was the most significant will be the model that was used. For this study, the Robust LM error model was used. The Robust LM error model takes into account the unobserved neighboring effect along with the unexplained portion for crime rates in the subject county. Along with looking at the Lagrange Multuplier, r^2 needs to be evaluated to find the goodness of fit. In addition to these steps, the multicollinearity condition number needs to be taken into consideration. If this number was over 30 then it means that there were variables being included in the regression that were correlated or measuring the same concept. The variables that were included for this analysis were Black, Hispanic, all poverty, no diploma, migration inflow, and migration outflow for both adults and juveniles for 1990, 2000, and 2010.

In order to find out if the model used was a good fit to what was being measured the r^2 needs to be looked at. The higher the adjusted r^2, the better the fit of the model meaning that a greater proportion of the variance was accounted for by the specific model. In Table 5, we can see that over time the fit of the model decreases meaning that the spatial regression model does not improve predictions over the mean model. The model fits best in 1990 but for each of the dependent variables, the goodness of fit decreases over time. With the decrease in the goodness of fit, it means that the variables are losing their explanatory power after 1990.

Table 5: Goodness of Fit (Adjusted r^2)						
	All Crime Adult	All Crime Juvenile	Violent Crime Adult	Violent Crime Juvenile	Property Crime Adult	Property Crime Juvenile
1990	0.54	0.38	0.41	0.39	0.58	0.38
2000	0.22	0.21	0.39	0.19	0.25	0.14
2010	0.16	0.17	0.34	0.20	0.25	0.14

After the goodness of fit was taken into account, the multicollinearity condition number was looked at. For all of the independent variables, the multicollinearity condition number was under 18. This means that the independent variables that were analyzed showed that they were not measuring the same concept and were not correlated to each other.

Table 6 shows the results of the spatial regression model estimates for adult crimes. All six dependent variables showed that the coefficients were greater for adults than for juveniles because of the size of the dependent variables. The crime rates per 100,000 population were much lower for juveniles compared to adults. When looking at ethnic heterogeneity, "Black" and "Hispanic" variables had statistically significant coefficients with the expected positive signs for all years and all crimes for both adults and juveniles. All coefficients were positive meaning that crime rates would increase for every increase in the share of the population "Black" or "Hispanic". For all study periods, coefficients for "Adult Property Crime" were greater than the coefficients for "Adult Violent Crime" meaning that some increase in the share of "Black" or "Hispanic" population would result in more adult property crime than adult violent crime being committed. The same pattern can be found for juvenile crimes for all three years (Table 7). The increase in ethnic heterogeneity results in more property crime than violent crime being committed. These two variables support social disorganization theory with their expected signs for both types of crimes and all three years.

Table 6: Spatial Regression Model Estimates (Adult Crime)						
	1990		2000		2010	
	Violent Crime	Property Crime	Violent Crime	Property Crime	Violent Crime	Property Crime
Constant	-103.7***	-257.2***	34.8**	230.3***	53.4***	179.8***
Black	200.7***	996.2***	278.5***	430.4***	217.0***	293.7***
Hispanic	243.3***	733.6***	121.9***	268.0***	112.8***	200.6***
All Poverty	-2.9	-17.5	86.4*	-101.1	218.9***	558.6***
No Diploma	1391.6***	1364.2***	211.8***	-76.7	-51.0	-490.5**
Migration Inflow	601.9*	4619.4***	-77.6	-349.5	290.0	778.0
Migration Outflow	1119.5***	7486.7***	629.2	1194.7	-411.6	772.9
Spatial Error	0.68***	0.71***	0.72***	0.66***	0.70***	0.70***
* P ≤ 0.05 ** P ≤ 0.01 *** P ≤ 0.001						

When looking at the socioeconomic status variables of “All Poverty” and “No Diploma”, it was interesting to see the significance change depending on the year being looked at. For “All Poverty”, coefficients for both types of adult crime (violent and property) in 1990 were not significant whereas the coefficient for both types of adult crime (violent and property) were significant with expected positive signs in 2010. During 2000, the results were mixed. For violent crime the coefficient was significant with the expected positive sign while for property crime the coefficient was not significant. The significant and positive coefficients mean that crimes rates would increase for the increase in the share of the population “All Poverty”. For juvenile crimes, “All Poverty” variable has a significant and negative coefficient for property crime in

1990 and has changed to a significant and positive coefficient in 2010. None of the coefficients for juvenile violent crime for the three years was significant.

Table 7: Spatial Regression Model Estimates (Juvenile Crime)

	1990		2000		2010	
	Violent Crime	Property Crime	Violent Crime	Property Crime	Violent Crime	Property Crime
Constant	-0.0001***	-0.0008***	0.0001***	0.002***	0.00001***	0.0007***
Black	0.0006***	0.002***	0.0004***	0.001***	0.0004***	0.001***
Hispanic	0.0005***	0.003***	0.0004***	0.002***	0.0003***	0.001***
All Poverty	0.000003	-0.0003*	-0.0000009	-0.001**	-0.000007	0.0007*
No Diploma	-0.000003	0.006***	-0.0001	-0.003***	-0.0003**	-0.004***
Migration Inflow	0.005***	0.007*	-0.003***	-0.02***	0.0006	0.0006
Migration Outflow	0.004***	0.04***	0.004*	0.01**	-0.002**	0.002
Spatial Error	0.62***	0.72***	0.56***	0.56***	0.57***	0.52***
* P ≤ 0.05 ** P ≤ 0.01 *** P ≤ 0.001						

For “No Diploma”, the coefficients both adult crimes (violent and property) were significant and positive in 1990 but this changes in 2000 and 2010. In 2000, the coefficient for violent crime was significant and positive while for 2010, the coefficient for property crime was significant and negative. The negative coefficient means that with the increase in the share of the population of “No Diploma” the property crime rates would decrease. For juvenile crimes, all coefficients were negative for violent crime but only the coefficient in 2010 was significant. For property crime all coefficients were significant for property crime but the sign of the coefficient was different. In 1990, the coefficient was positive while for 2000 and 2010 the coefficient was negative. This means that in 1990, the increase in the share of the population of “No Diploma” is correlated with an increase in the property crime rate while for 2000 and 2010, the increase in the share of the population of “No Diploma” is correlated with a decrease in the property crime rates.

When looking at the residential mobility variables of “Migration Inflow” and “Migration Outflow”, results show for both adult crime types (violent and property) were significant with expected positive signs in 1990. This means that the increase in the share of the population of “Migration Inflow” and “Migration Outflow” is correlated with an increase in the violent crime rate and property crime rate. All coefficients for both adult crime types (violent and property) were not significant for 2000 and 2010. For juvenile crimes, coefficients were significant for both crime types (violent and property) for 1990 and 2000. All of the coefficients in 1990 were positive for “Migration Inflow” and “Migration Outflow” but for 2000, the “Migration Inflow” coefficients were negative while the coefficients for “Migration Outflow” were positive. The results for 2010 show that only “Migration Outflow” for juvenile violent crime was significant and has a negative sign while all other coefficients were not significant. This means that the increase in the share of the population of “Migration Outflow” is correlated with a decrease in the violent crime rate.

From these spatial regression model estimates, it can be concluded that the three overall variable types (ethnic heterogeneity, socioeconomic status, and residential mobility) did not support Shaw and McKay’s Social Disorganization Theory. Ethnic heterogeneity was the only variable that supported this theory with its predicted coefficient signs for both adults and juveniles but the socioeconomic status and residential mobility variables did not support the theory at all. From the results of the spatial regression model, it can be concluded that social disorganization theory fits best in

1990 with the expected signs but for all other years social disorganization theory does not fit with the model. Other than "All Poverty", which is only important in 2010, the other variables based on social disorganization theory lost its explanatory power for crime rates. These results confirm the results from the goodness of fit test that was performed earlier. Based on the results of this study, when looking at the three overall variable types, their effect on adult and juvenile, violent and property crime varies from year to year.

<u>Results of Metropolitan versus Nonmetropolitan Areas</u>

After running the spatial regressions and testing it against Shaw and McKay's Social Disorganization Theory, metropolitan counties were looked at. Being classified as an MSA county proved to be significant when tested with the variables for Social Disorganization Theory.

For both crime types (violent and property), all coefficients were significant and positive. This means that being classified as an MSA county contributes to a rise in the given crime rates and the amount of urban density was important to consider when looking at crime rates in a given county. For all study periods, coefficients for "Adult Property Crime" were greater than the coefficients for "Adult Violent Crime" meaning that some increase in the share of MSA counties would result in more adult property crime than adult violent crime being committed. The coefficient for "Adult Violent Crime" is the highest in 1990 but for "Adult Property Crime", the coefficients are consistently high. These results were also true for "Juvenile Property Crime" and "Juvenile Violent Crime" as seen in Table 8.

Table 8: Spatial Regression Model Estimates MSA Counties						
	1990		2000		2010	
	Violent Crime	Property Crime	Violent Crime	Property Crime	Violent Crime	Property Crime
Adult	26.2***	60.4***	8.8*	30.2***	8.7*	70.3***
Juvenile	0.00004***	0.0005***	0.00004***	0.0003***	0.00004***	0.0002***
* P ≤ 0.05 ** P ≤ 0.01 *** P ≤ 0.001						

CHAPTER 5

DISCUSSION AND CONCLUSION

Summary of Findings

Based on the findings of this study, it can be concluded that higher violent crime rates and higher property crime rates were concentrated along the coastlines of the United States. The Midwest shows low clusters of crime rates throughout all years of the study but this could change if data for Illinois was included for analysis. This was in opposition to early research that states that high violent crime rates will be along the coastlines and high property crime rates will be located in the Midwest (FBI, 2011).

When looking at the different time periods (1990, 2000, and 2010), there has been a shift from the West Coast to the South and East Coast with the most amount of increase in crime rates coming in between the years 1990 and 2000. This can be seen in the figures for the exploratory spatial data analysis at the local level. For adult property crime rates, they were mainly concentrated along the West coast but by 2010, they were concentrated mostly along the East coast. Areas that were labeled as being low in crime rates have remained the same but there has also been a shift of higher crime rate counties surrounding those previously low crime rate counties. The effect on juveniles has not been as dramatic. Areas that were classified as having low and high crime rates have remained the same with only some areas increasing or decreasing in their given category.

Spatial regressions showed that the coefficients were greater for adults than for juveniles because of the size of the dependent variables. Also, no matter what variable was being examined, an increase in the share of the population of the given variable would result in more property crime than violent crime being committed. When looking at the results for ethnic heterogeneity, “Black” and “Hispanic” variables proved to be statistically significant and positive for adults and juveniles. This means the greater the share of the population of “Black” and “Hispanic” would result in more crime being committed. For the socioeconomic variables, “All Poverty” and “No Diploma”, results varied by the different study years. Both variables had significant coefficients in all years except in 1990 for “All Poverty”. The interesting finding was with “No Diploma” in 2010. This is the only coefficient that is significant and negative. This means that with the increase in the share of the population of “No Diploma” the property crime rates would decrease. When looking at the residential mobility variables, “Migration Inflow” and “Migration Outflow”, both crime types were significant with positive coefficients for 1990 while for 2000 and 2010 both crime types were not significant.

These spatial regression model estimates show that Social Disorganization Theory is not supported. This may be because of the unit of analysis. Social disorganization theory is originally measured at the neighborhood level. By using county level data, it may not be appropriate to accurately test social disorganization theory. When looking at the specific variables, ethnic heterogeneity is supported for both adults and juveniles but socioeconomic status and residential mobility are not supported.

The last comparison that was being made was the distinction between metropolitan counties (MSA) and nonmetropolitan counties (non-MSA). Being classified as an MSA county proved to be significant for all years and crime types. All crime types and years were significant and positive. This was showing that MSA counties do lead to increased crime rates while non-MSA counties do not. This may be because MSAs have a higher chance at having increased rates of ethnic heterogeneity, lower socioeconomic status, and higher residential mobility when compared to other counties that have smaller cities even though these were controlled for in the study. Further testing is needed in this area to find out if being classified as an MSA or non-MSA county in certain regions of the United States will contribute to more crime being committed in that specific area.

Based on the findings of this study, social disorganization theory may not be the most appropriate theory to test these specific variables against. Social disorganization theory is not supported with these results, so other theories need to be looked at to determine if this specific model will fit with other theories. The first determining factor for testing another theory will be the unit of analysis. Since this data deals with county level data, the theory would also need to reflect that.

Major Implications of the Current Study

From this study, temporal shifts of spatial distribution in crime rates were identified and this will guide policy makers to reallocate limited resources effectively into those areas. Many of the high crime areas tended to be in counties with a metropolitan statistical area within the boundaries of the county. The spatial regression model estimates showed that, those counties associated with an MSA were more likely to have higher crime when paired with the variables for Social Disorganization Theory (ethnic heterogeneity, socioeconomic status, and residential mobility). However, there were non-MSA counties that have high crime rates as well. Also there were many counties, regardless of MSA and non-MSA distinction, that have lower crime rates. This shows that there may be different procedures and policies both in metropolitan and nonmetropolitan areas that may already be effective at controlling region specific crime rates. For example, cities within a county may have already fine-tuned policies that work effectively to reduce specific types of crime which result in lower overall crime rates. A nationwide policy may not need to be put into effect because there were counties that were adequately managing crime in their own areas but instead county level policies can be implemented, especially in counties classified as an MSA county since there tend to be higher crime rates in those specific counties. There are some broader regions in the United States that may get some help reducing crime rates from regional policies such as those with higher violent crime rates and property crime rates (Coastlines). Specific policies can be made for these two distinct areas based on the high levels of crime being committed there.

Data Limitations of Study

There were many limitations that were found within this study. The first has to deal with the data itself. When collecting national data especially from the Census, we were not getting the true number of responses to all the variables. For certain variables, we were only getting about a 10% response and the rest of the data was estimated. Specifically with the Census, they did not start asking about educational attainment until the 2000 survey but for 1990 there was a question about whether high school was completed for adults age 25 years and older. Also, the census did not ask about two or more races.

When collecting the crime data, it was important to note that data collected from UCR was not entirely accurate. UCR data was initially intended for use at the national level and when comparing across jurisdictions there may be problems because not all counties or agencies will report all crime that was actually happening. Also depending on the data that was being submitted, it may not be taken into consideration if there were too many data points missing.

To further limit this, when looking at county level data the analytical scale could either be too large or too small. This could either create geographic variations or hide them. Also with this level of data, it does not accurately reflect what Shaw and McKay originally thought of when they developed social disorganization theory. They looked at neighborhood structures and by using county level data it may not capture all of the processes that they originally wanted to capture. Based on the county level data used, policies can be created but this can prove to be a limitation because there are many different cities within a county and each one, often times, operates independently and differently from each other. Although county policies can be helpful, most policies are created at the municipal level.

There were some data points missing so it may not accurately reflect all of the spatial patterns that were involved. For example, Broomfield County, CO was not officially a county until 2001 so comparing data for 1990 and 2000 against 2010 was impossible. Also crime data was missing for Florida, Illinois, and Wisconsin in 2000 and for Florida and Illinois in 2010. This was problematic because there were two of the biggest cities in Florida (Miami) and Illinois (Chicago) that would help to explain if crime was higher or lower in these cities when compared to other cities.

Future Research

More research needs to be conducted in this area, especially when testing against the variables for social disorganization theory. Using different types of neighborhood structures could have yielded different spatial distribution patters of crime considering neighborhood effects and this could prove to support social disorganization theory. MSA and non-MSA counties can be looked at in more detail to find if specific cities are more vulnerable to higher crime rates.

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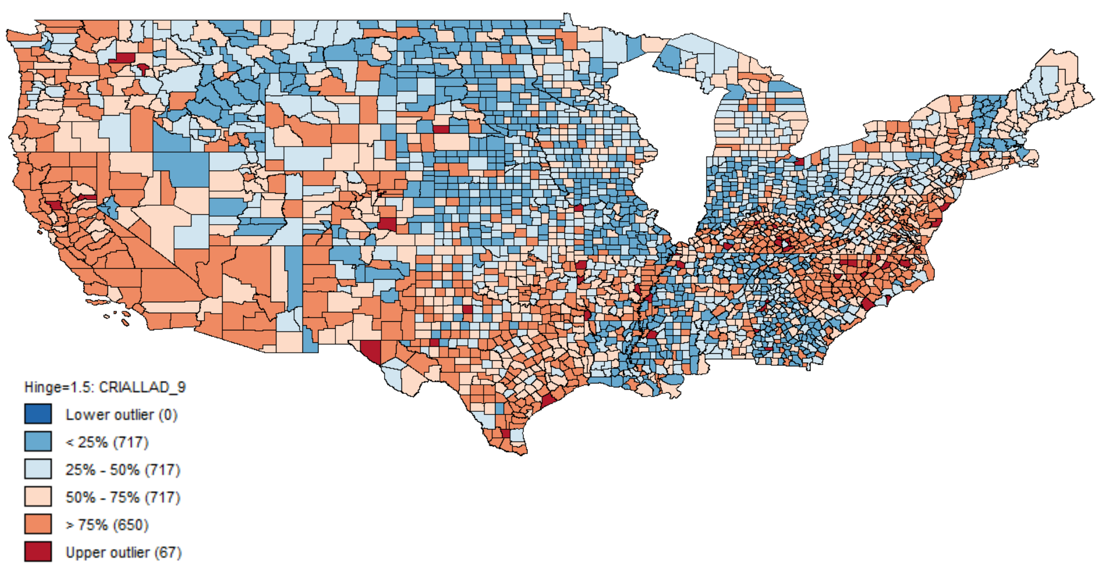
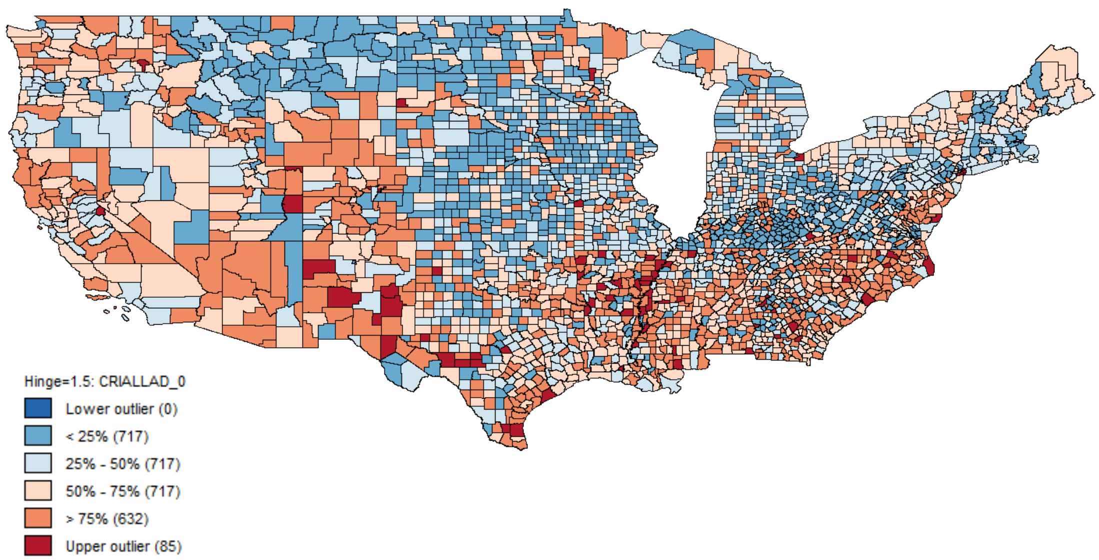
APPENDIX A SPATIAL DISTRIBUTION MAPS

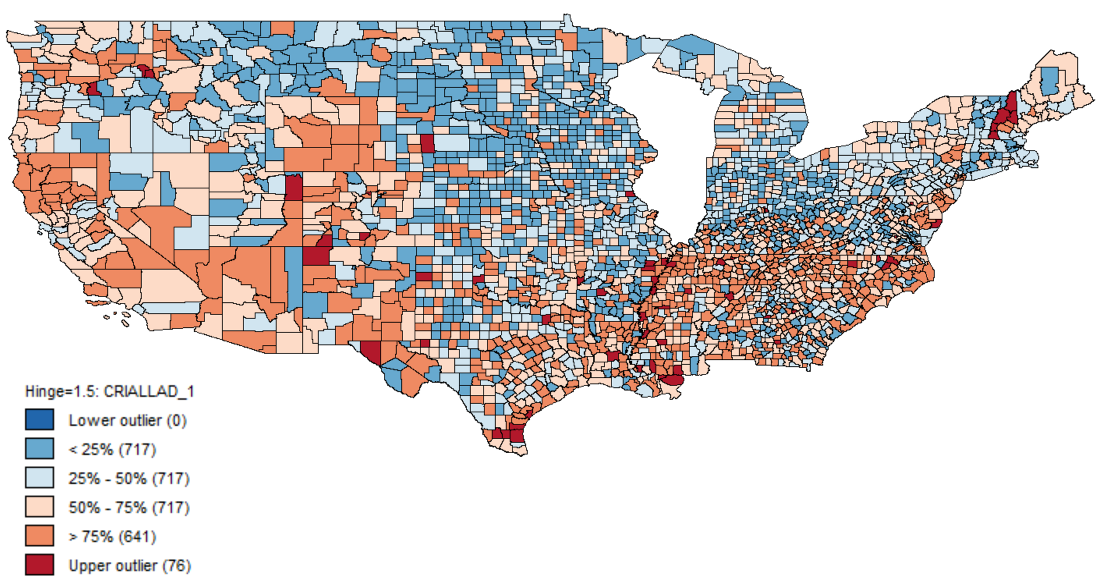
Map 1: Spatial Distribution All Crime Adult 1990



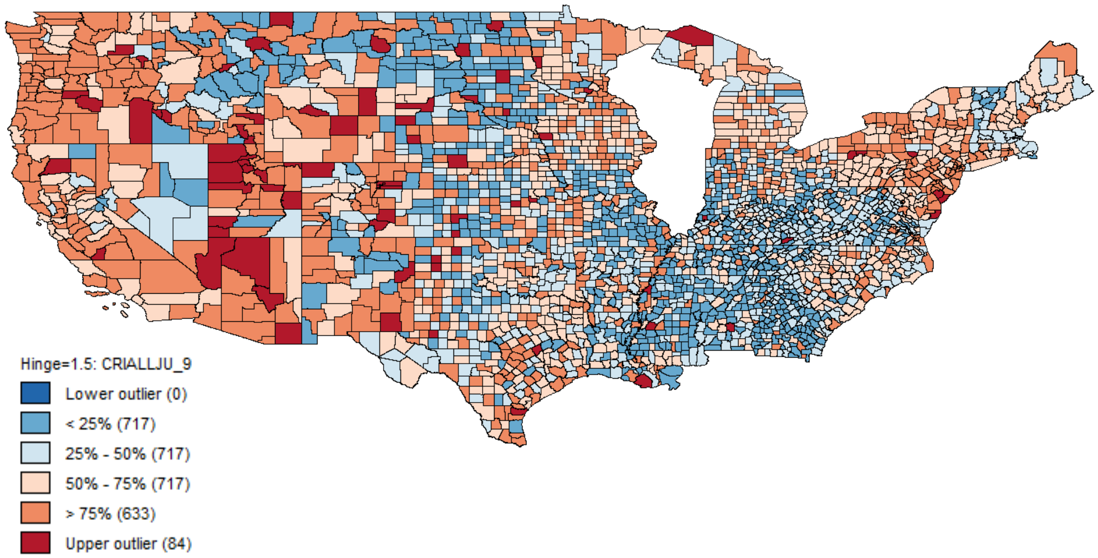
Map 2: Spatial Distribution All Crime Adult 2000



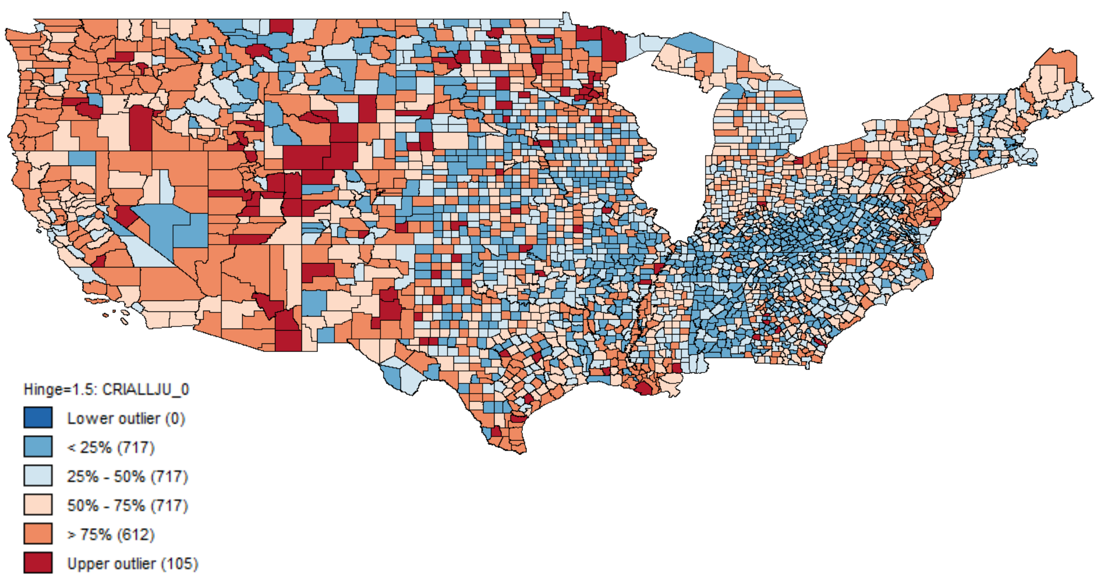
Map 3: Spatial Distribution All Crime Adult 2010



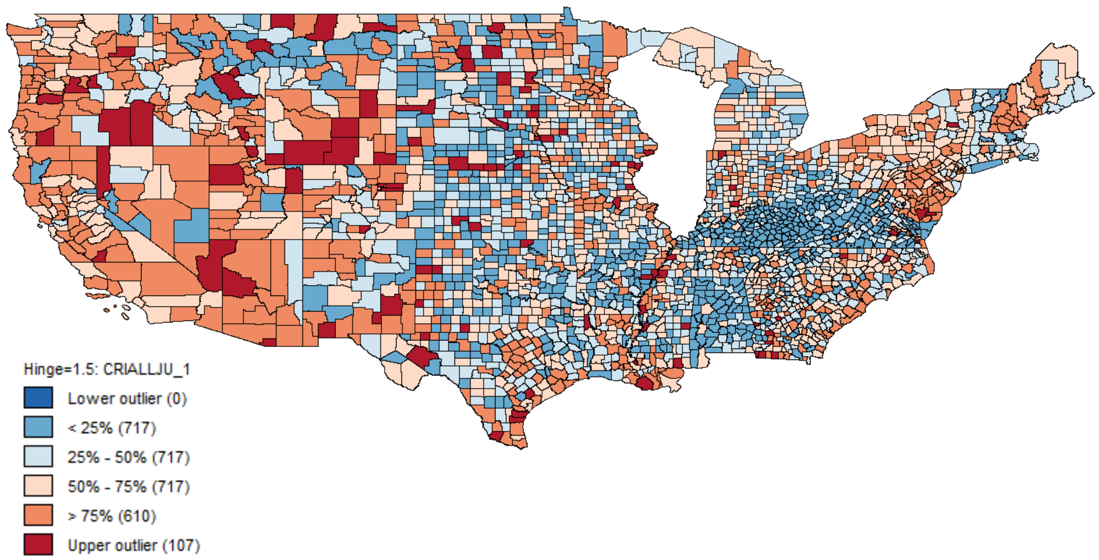
Map 4: Spatial Distribution All Crime Juvenile 1990



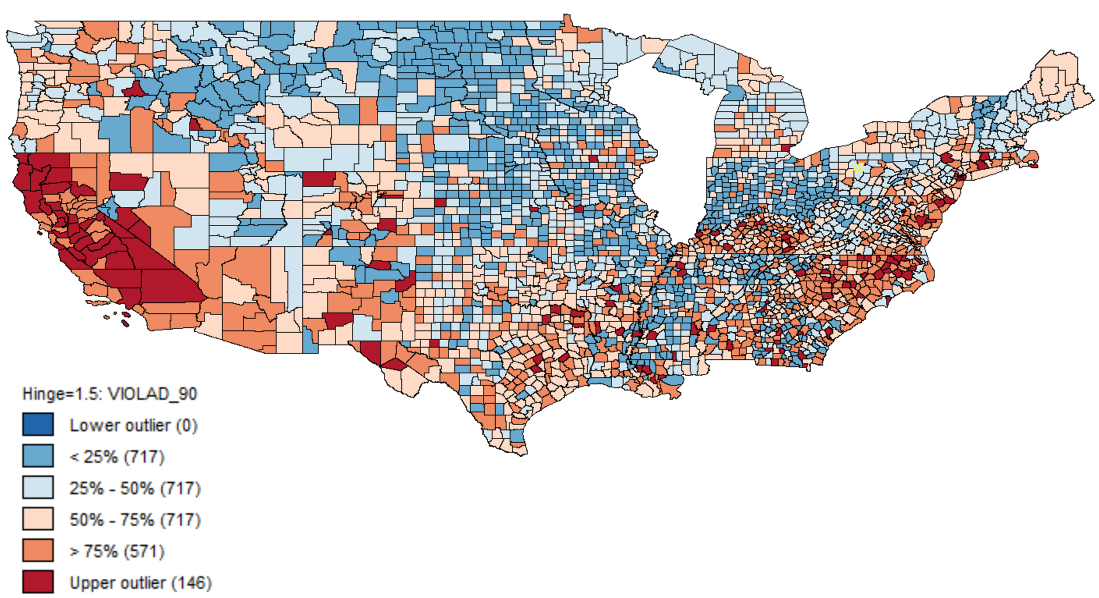
Map 5: Spatial Distribution All Crime Juvenile 2000



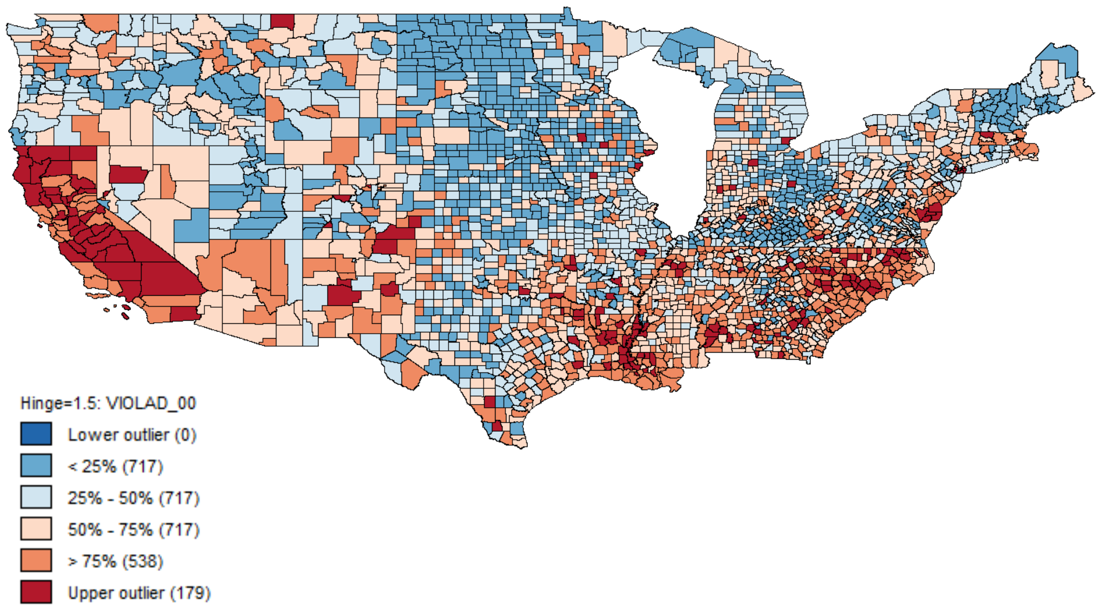
Map 6: Spatial Distribution All Crime Juvenile 2010



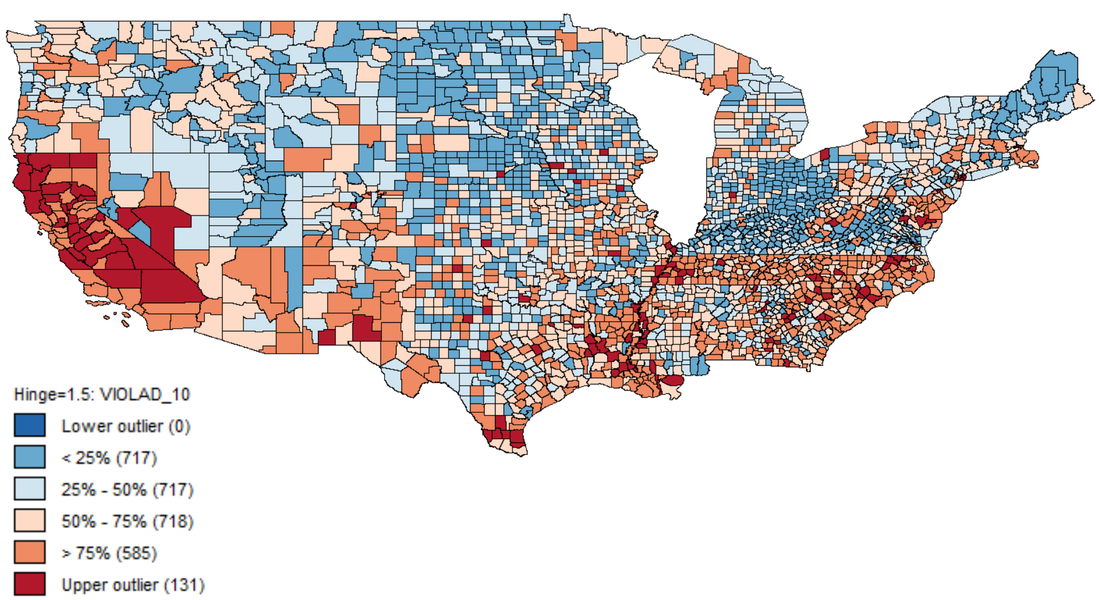
Map 7: Spatial Distribution Violent Crime Adult 1990



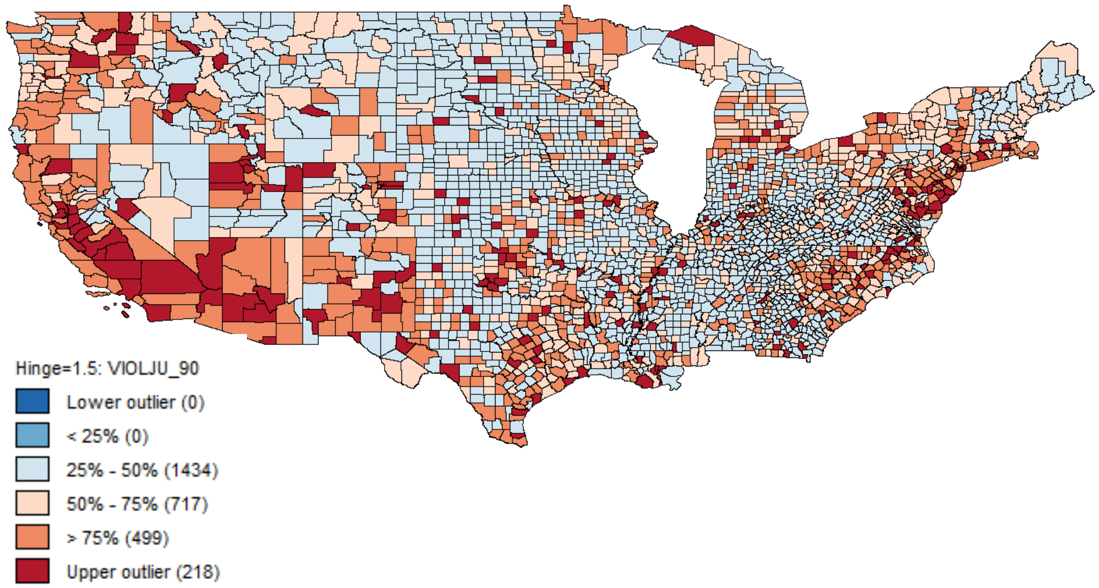
Map 8: Spatial Distribution Violent Crime Adult 2000



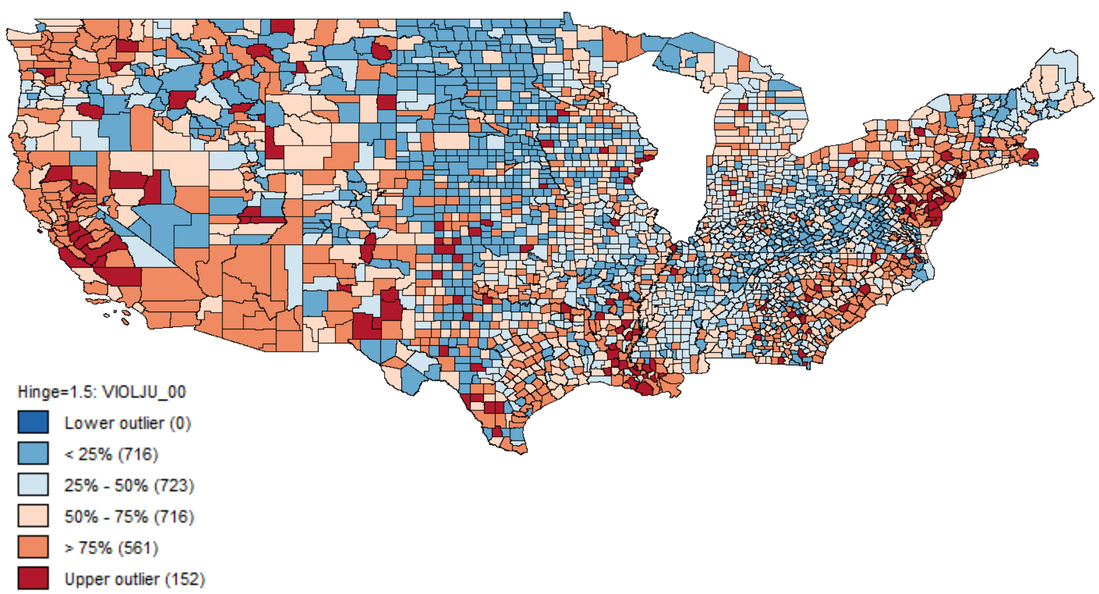
Map 9: Spatial Distribution Violent Crime Adult 2010



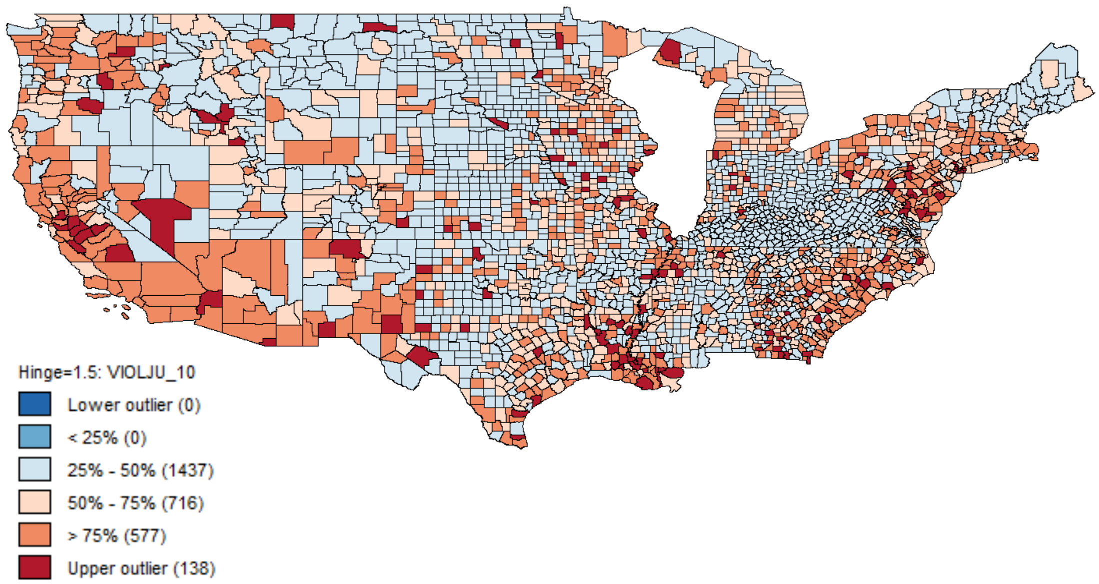
Map 10: Spatial Distribution Violent Crime Juvenile 1990



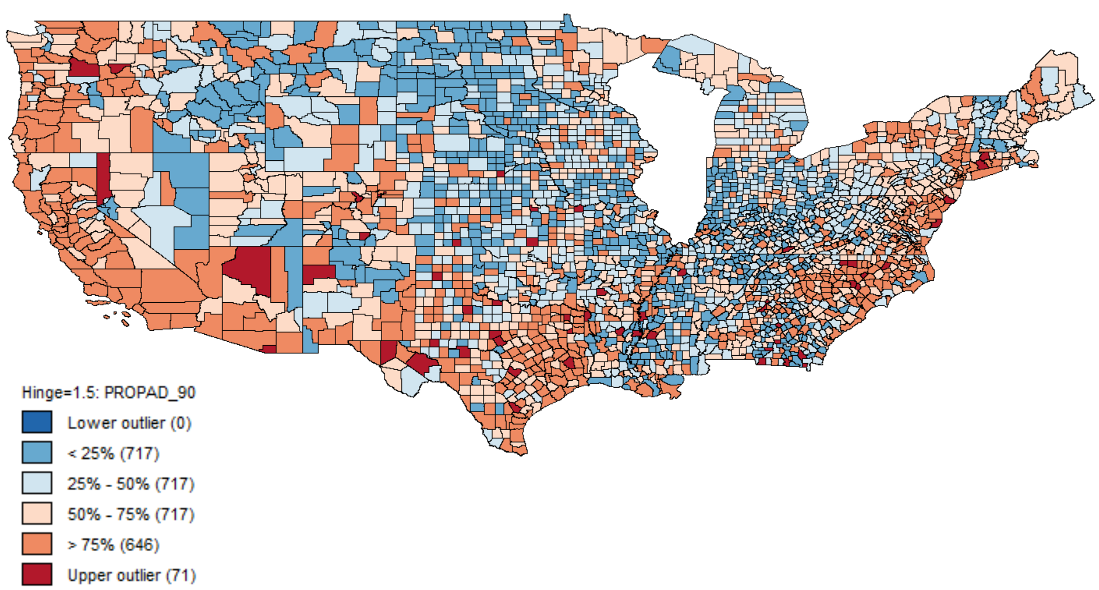
Map 11: Spatial Distribution Violent Crime Juvenile 2000



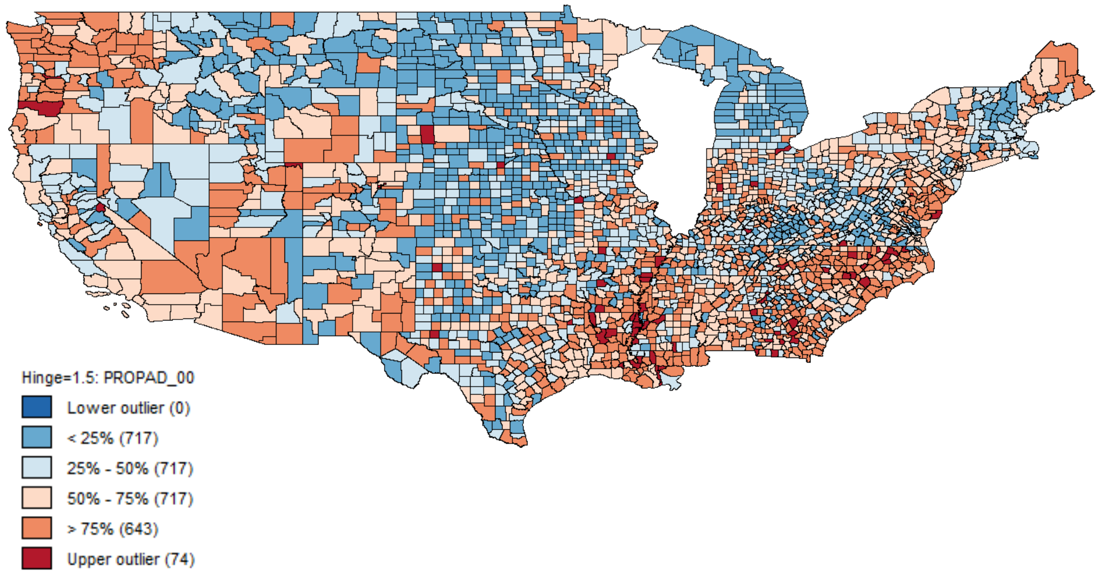
Map 12: Spatial Distribution Violent Crime Juvenile 2010



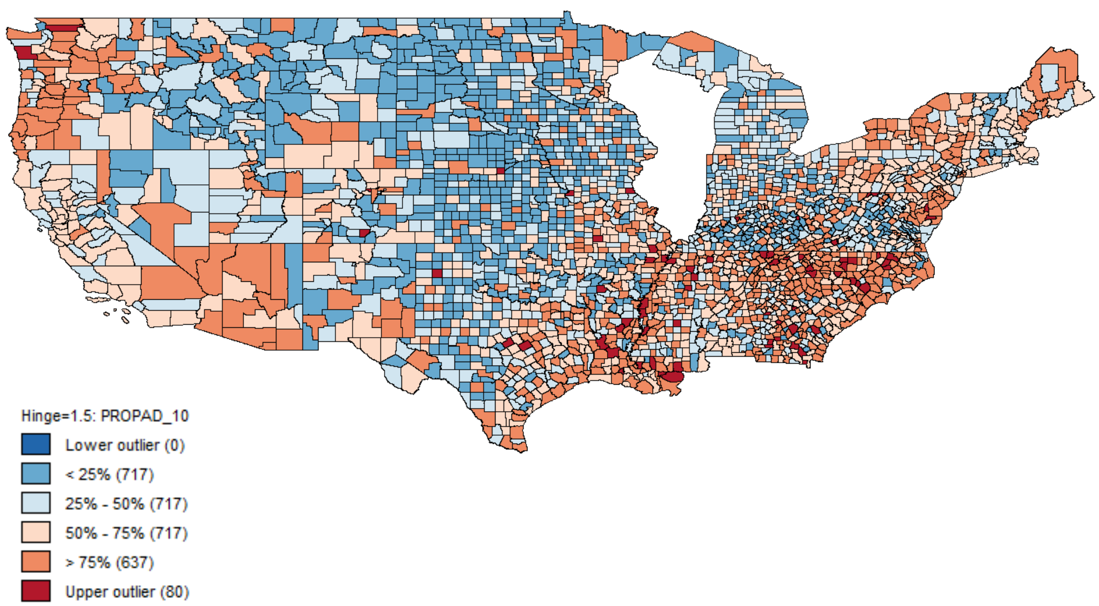
Map 13: Spatial Distribution Property Crime Adult 1990



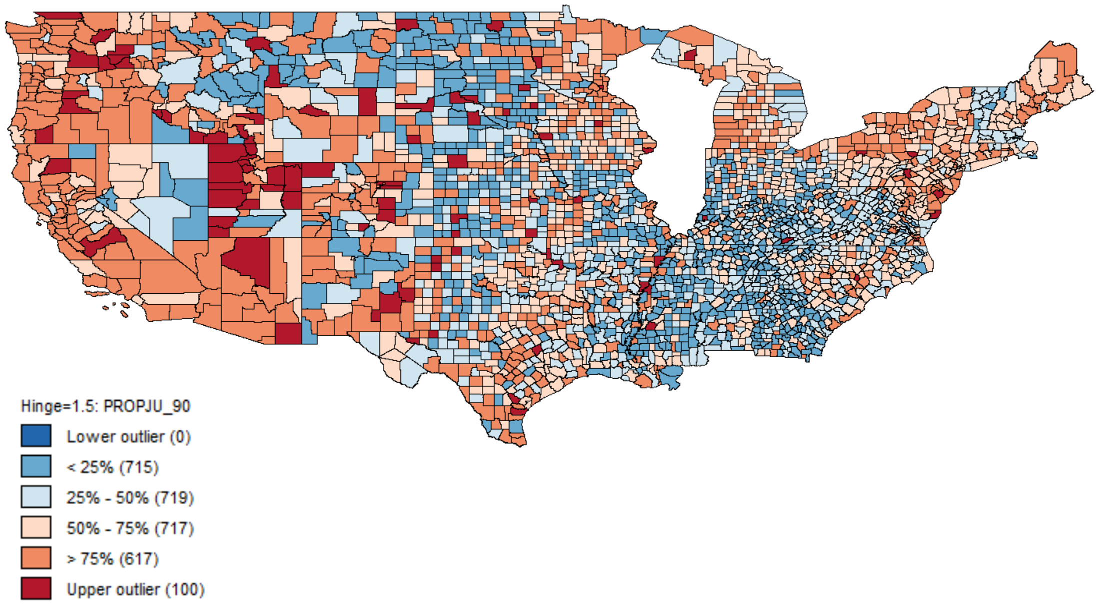
Map 14: Spatial Distribution Property Crime Adult 2000



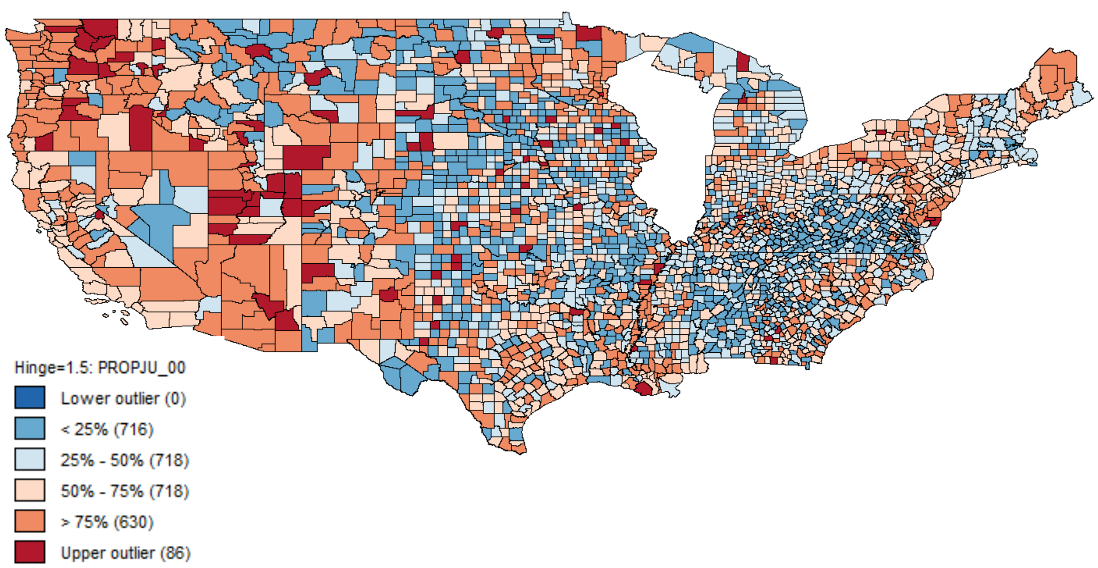
Map 15: Spatial Distribution Property Crime Adult 2010



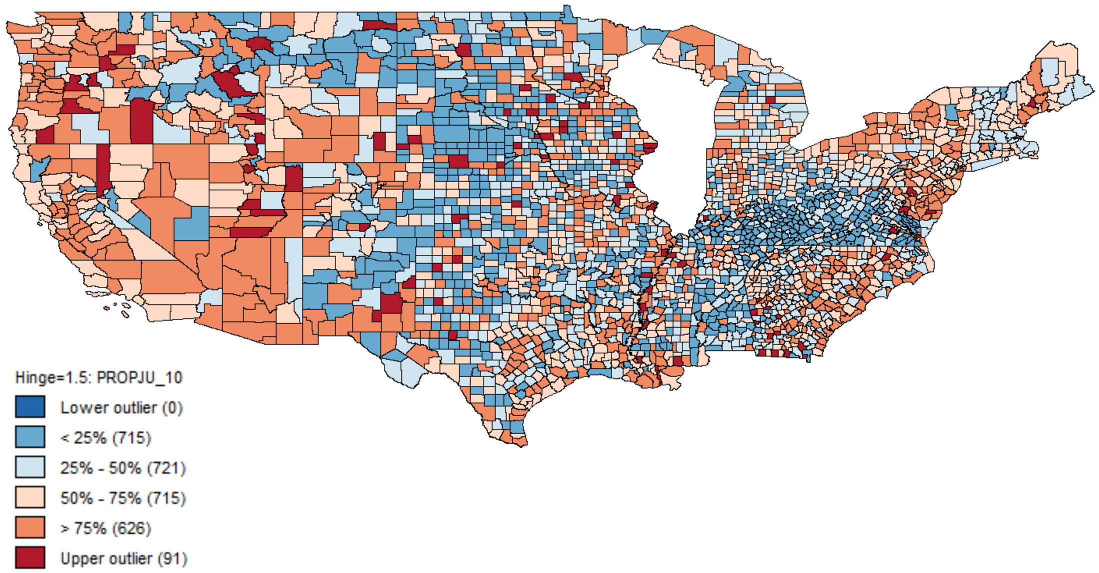
Map 16: Spatial Distribution Property Crime Juvenile 1990



Map 17: Spatial Distribution Property Crime Juvenile 2000

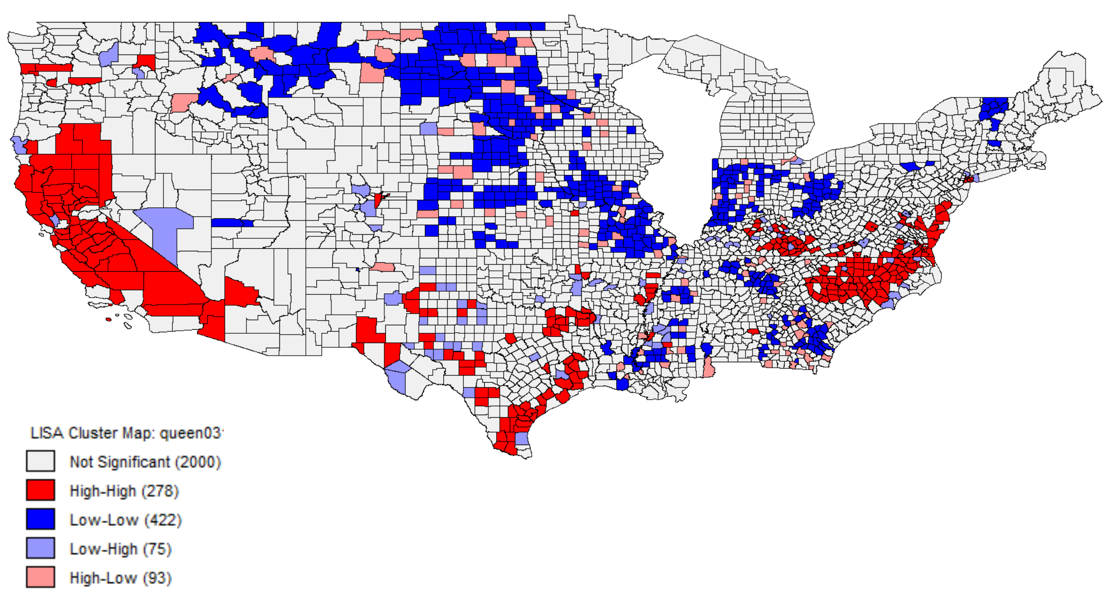


Map 18: Spatial Distribution Property Crime Juvenile 2010

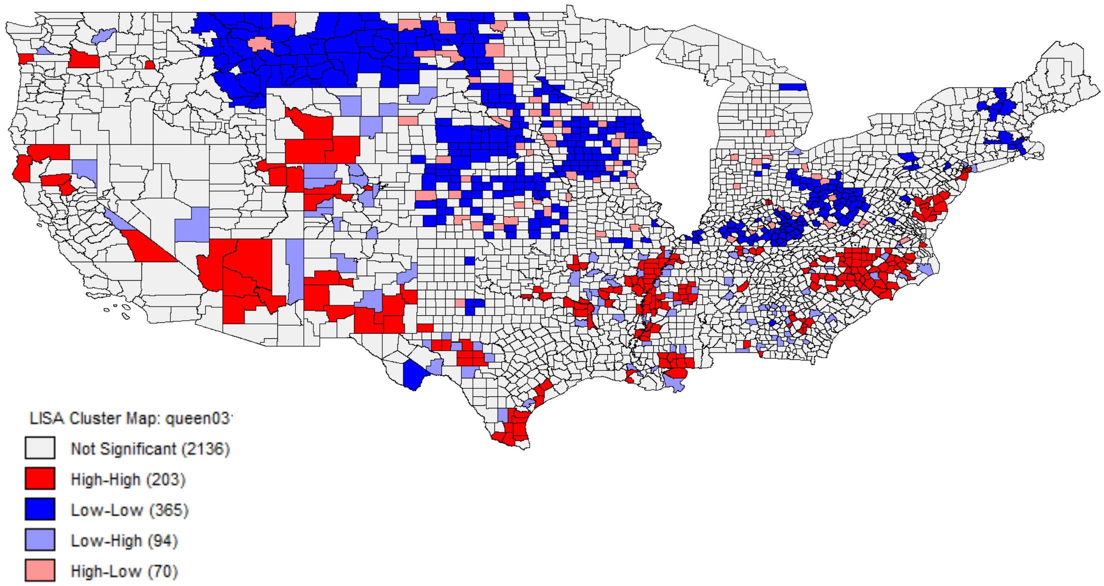


APPENDIX B LISA DISTRIBUTION MAPS

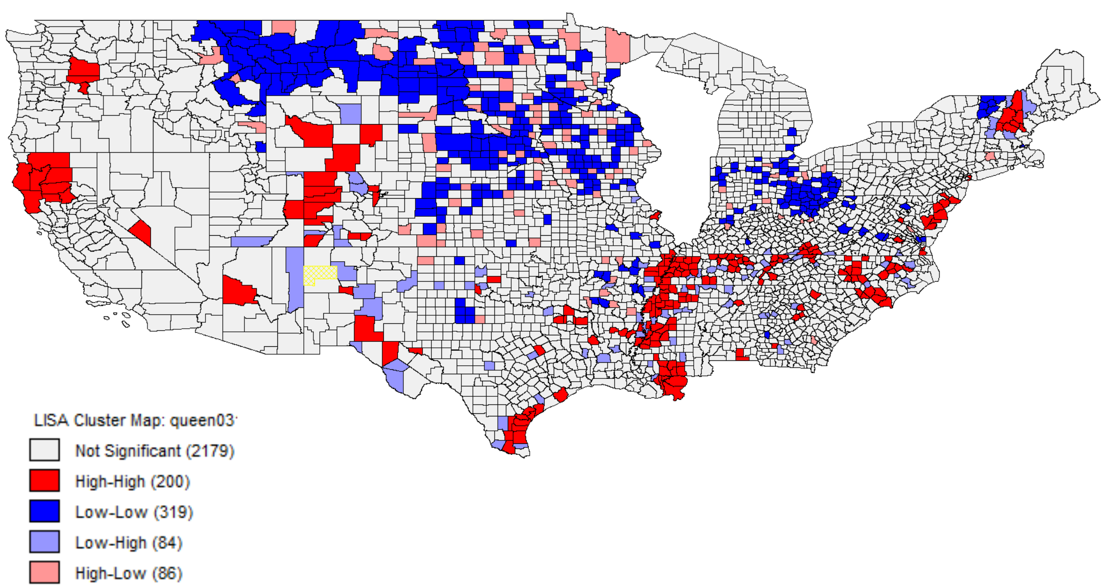
Map 19: LISA Distribution All Crime Adult 1990



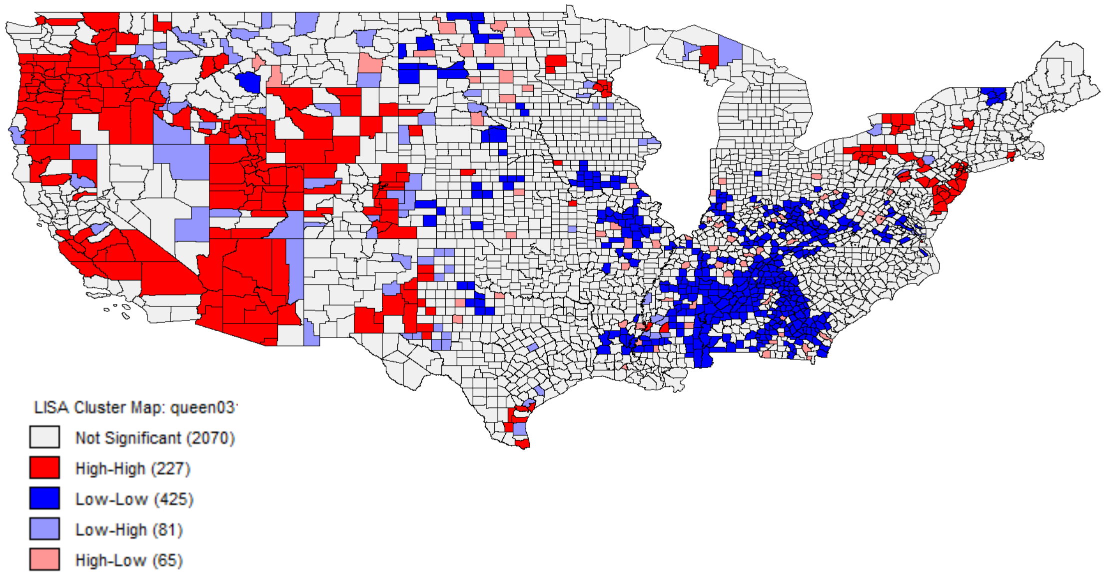
Map 20: LISA Distribution All Crime Adult 2000



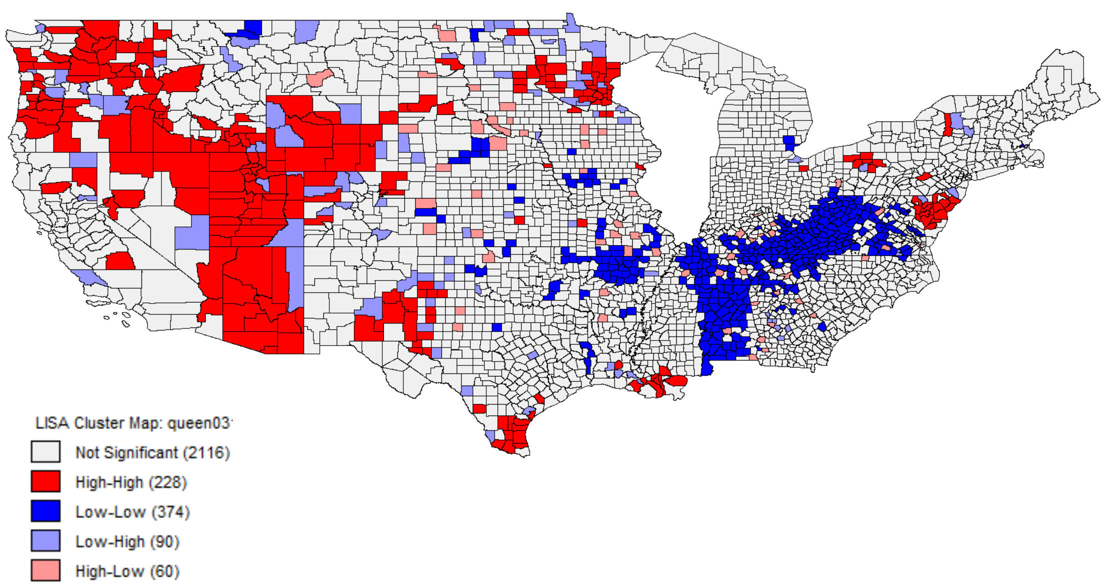
Map 21: LISA Distribution All Crime Adult 2010



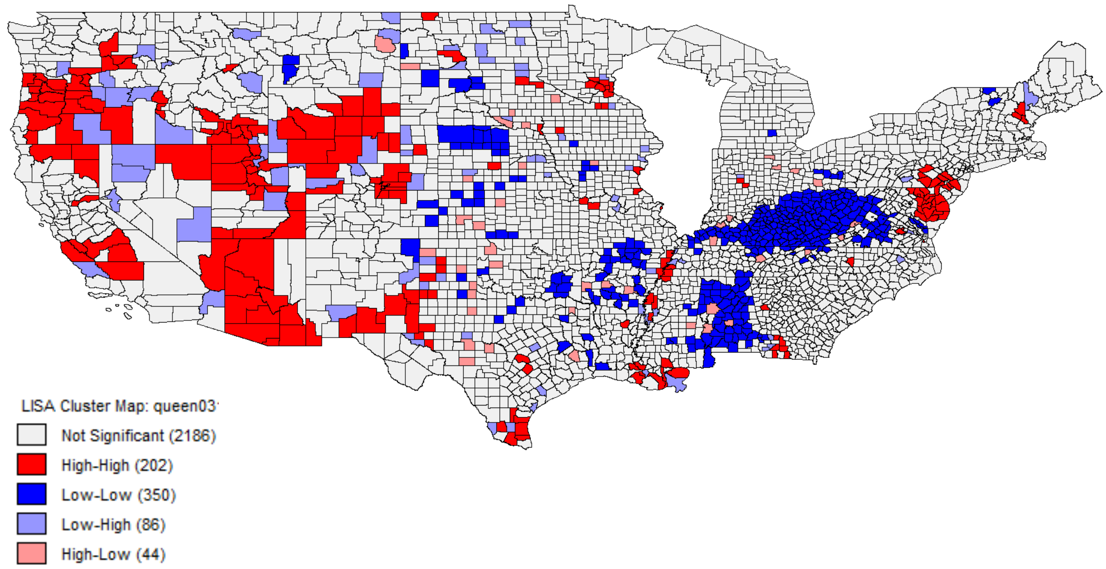
Map 22: LISA Distribution All Crime Juvenile 1990



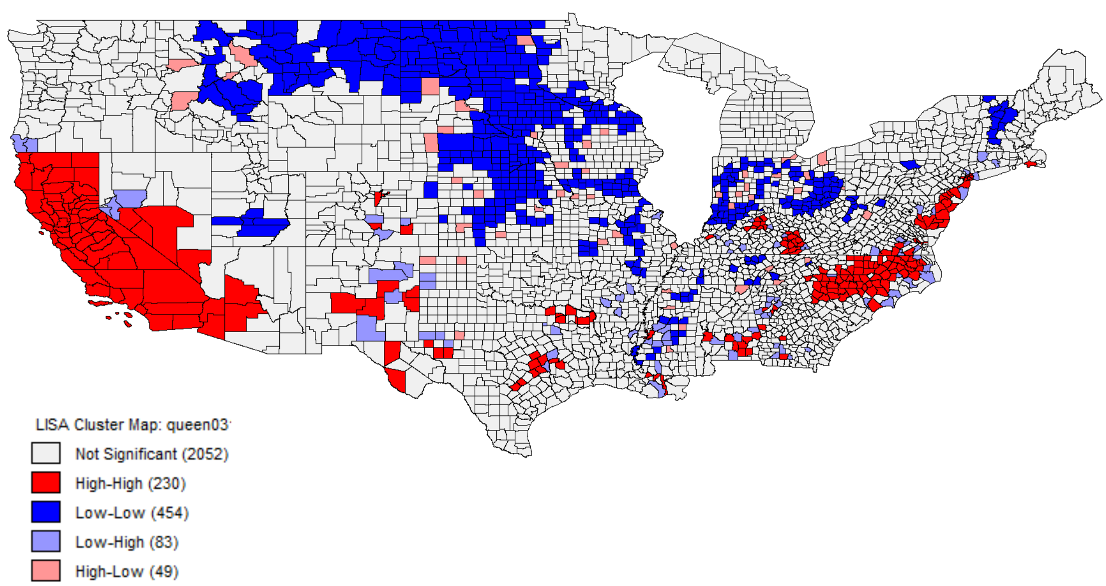
Map 23: LISA Distribution All Crime Juvenile 2000



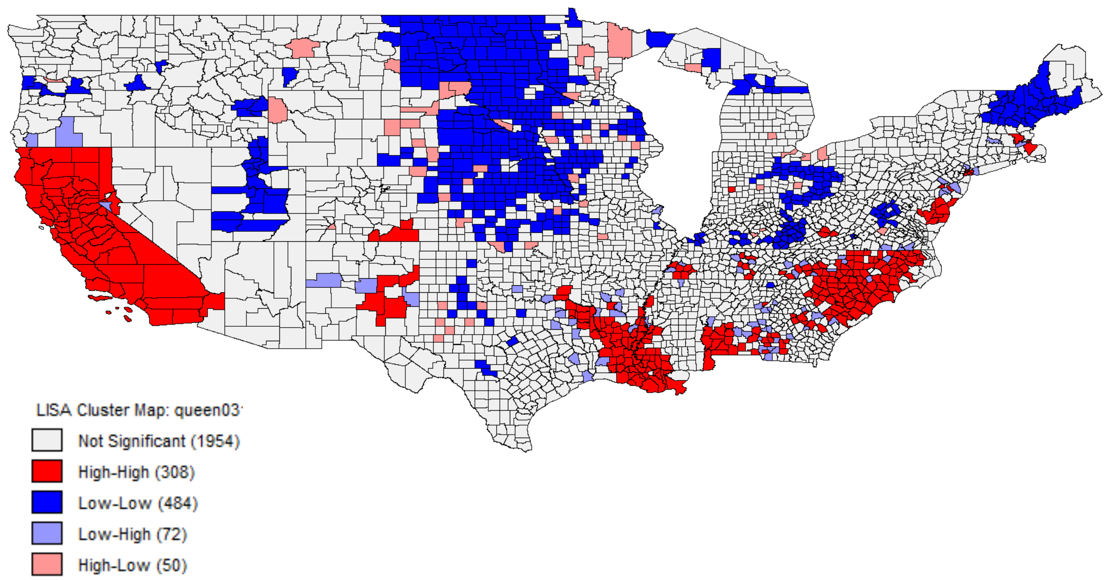
Map 24: LISA Distribution All Crime Juvenile 2010



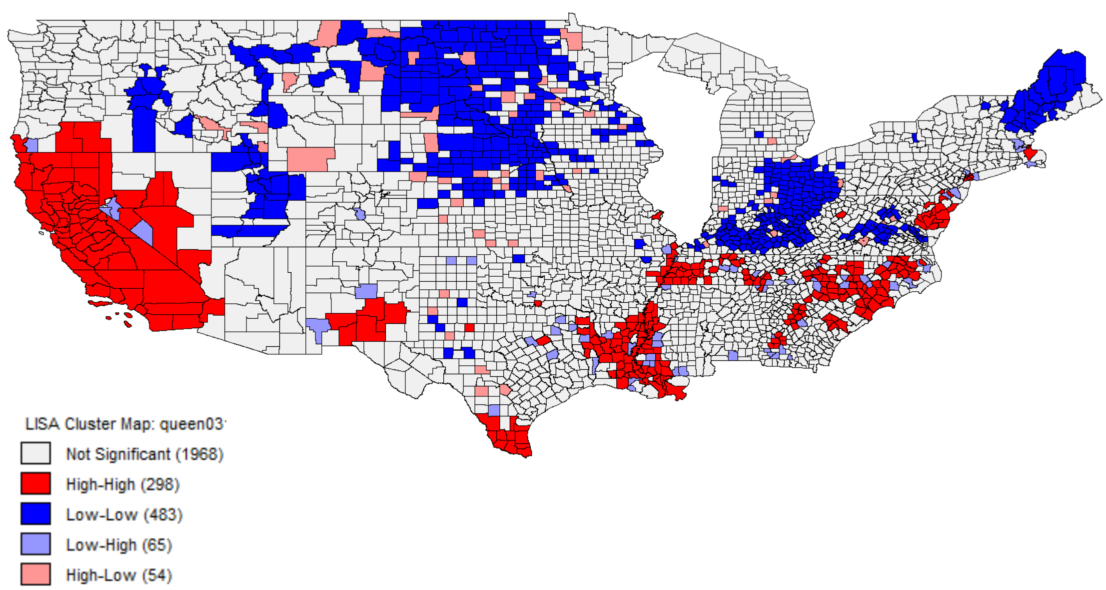
Map 25: LISA Distribution Violent Crime Adult 1990



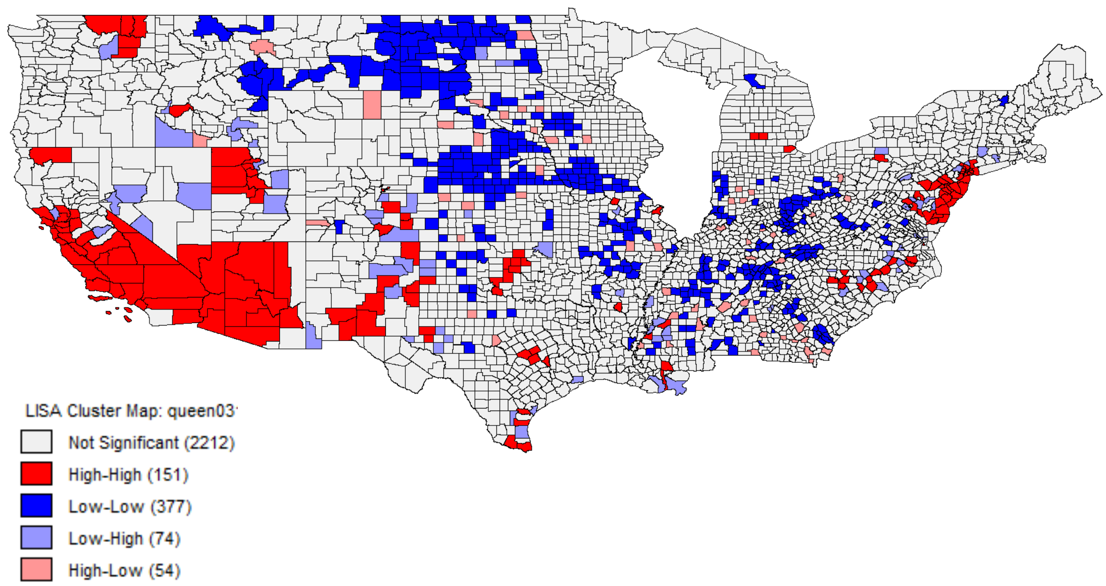
Map 26: LISA Distribution Violent Crime Adult 2000



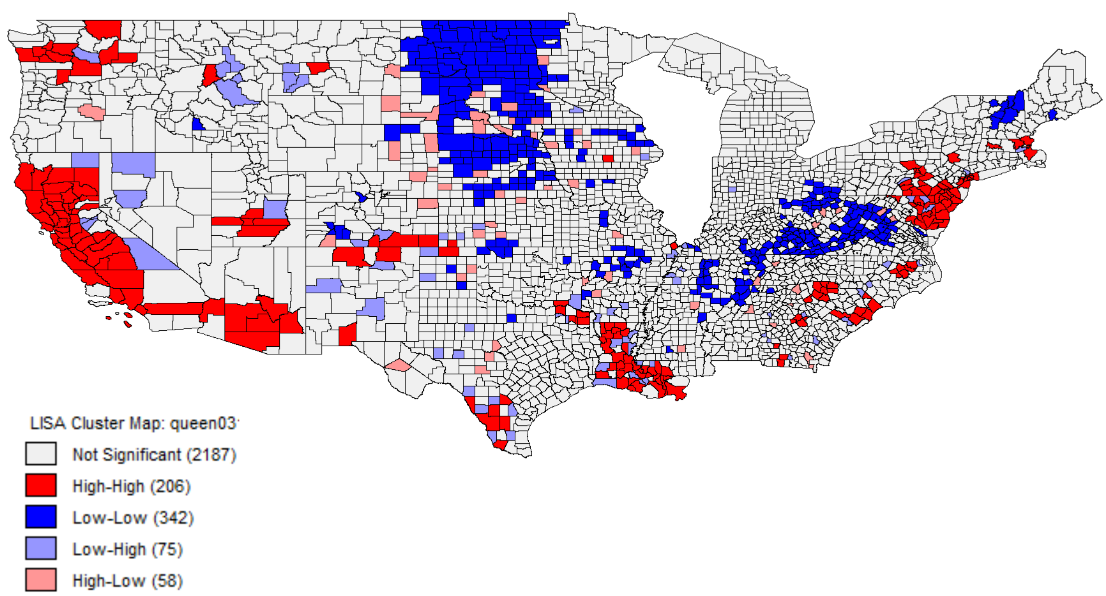
Map 27: LISA Distribution Violent Crime Adult 2010



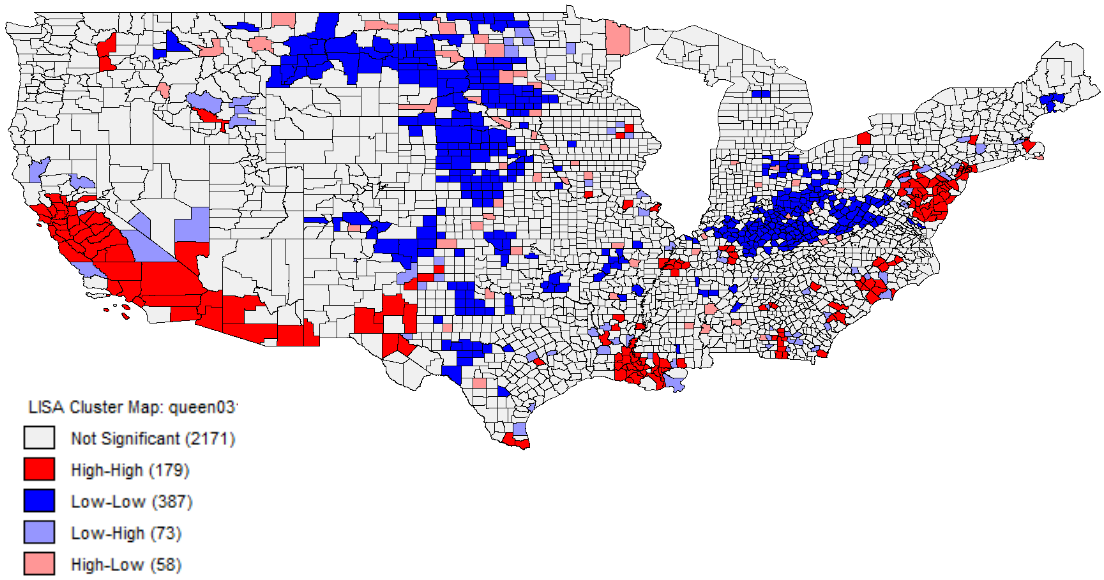
Map 28: LISA Distribution Violent Crime Juvenile 1990



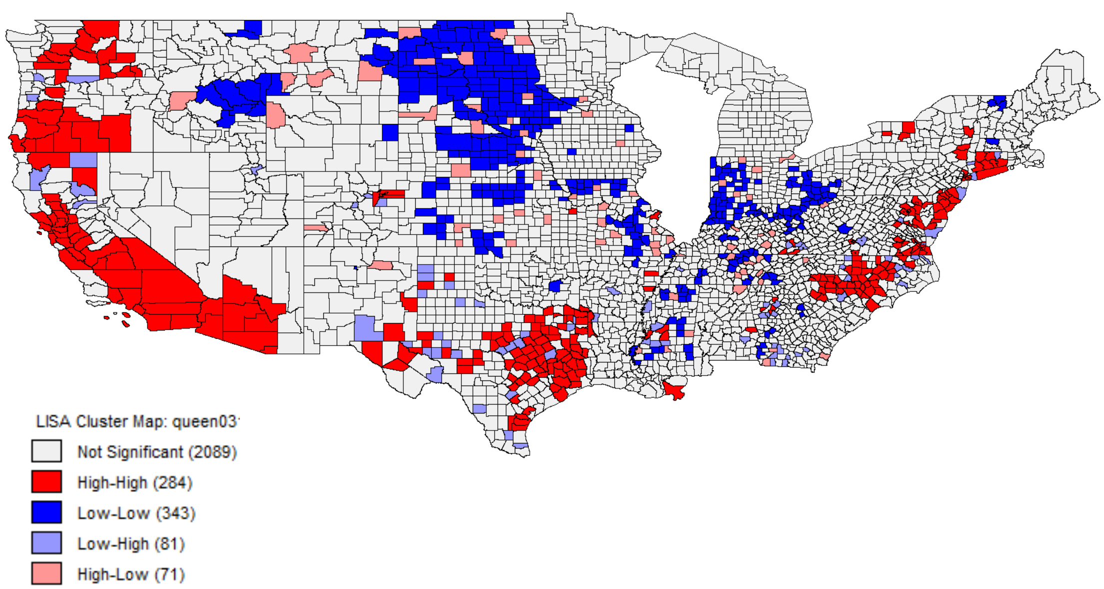
Map 29: LISA Distribution Violent Crime Juvenile 2000



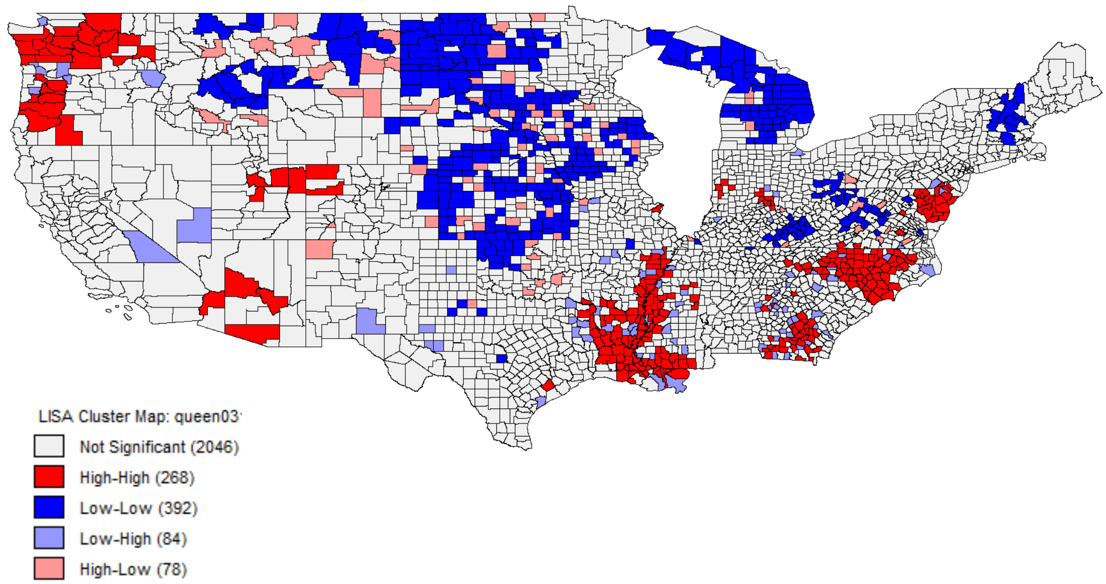
Map 30: LISA Distribution Violent Crime Juvenile 2010



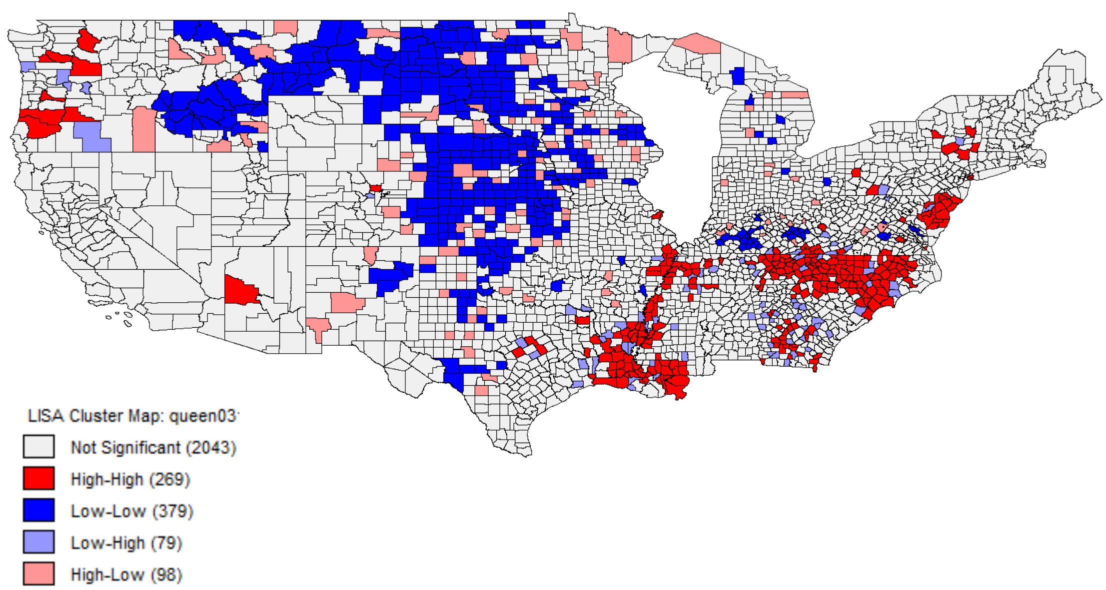
Map 31: LISA Distribution Property Crime Adult 1990



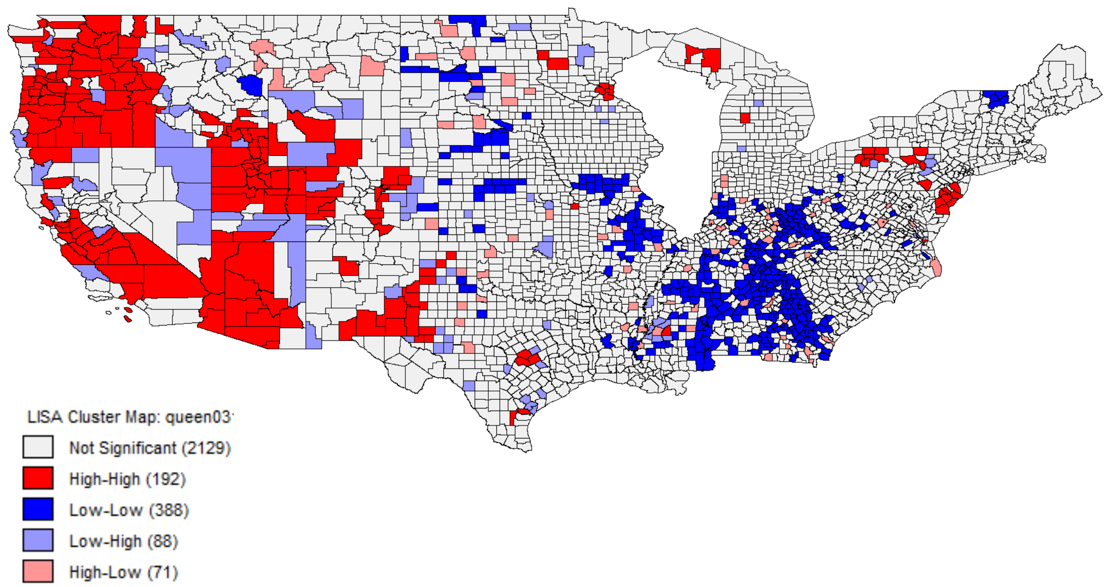
Map 32: LISA Distribution Property Crime Adult 2000



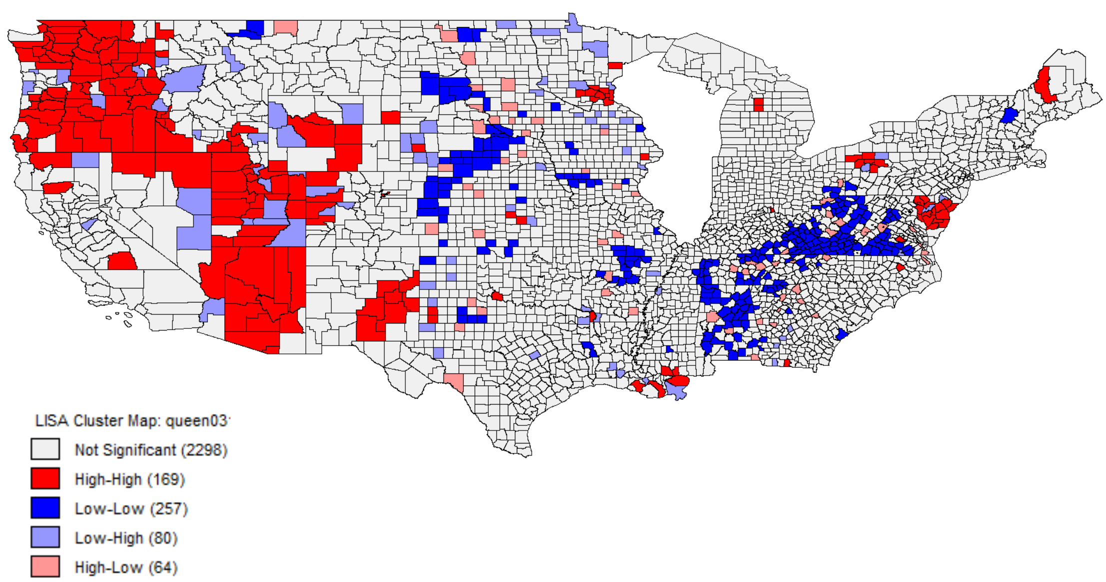
Map 33: LISA Distribution Property Crime Adult 2010



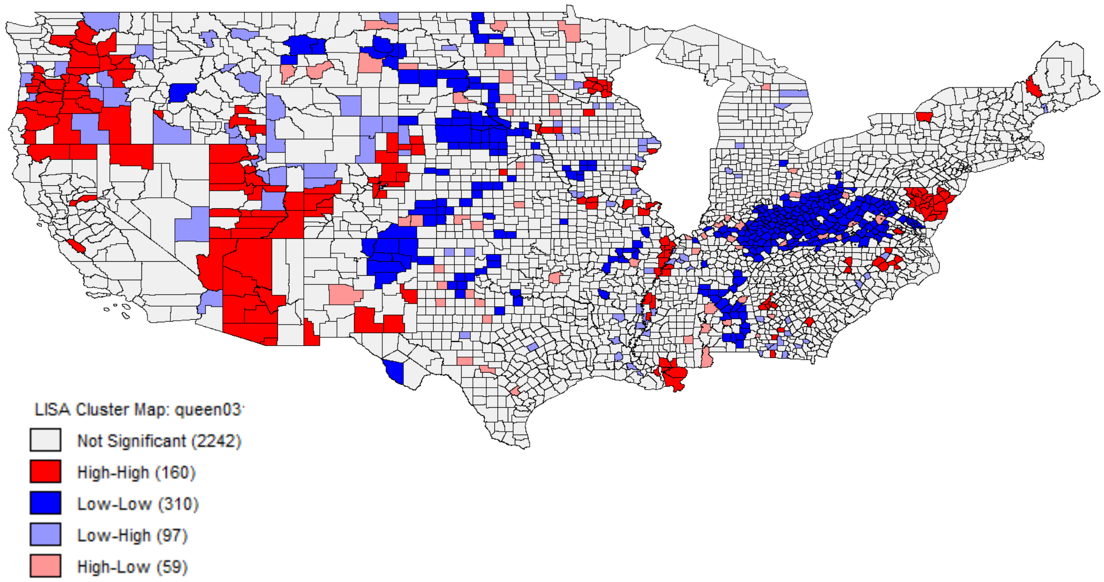
Map 34: LISA Distribution Property Crime Juvenile 1990



Map 35: LISA Distribution Property Crime Juvenile 2000



Map 36: LISA Distribution Property Crime Juvenile 2010



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Thesis Title:

A Spatial Analysis Test of Decennial Crime Patterns in the United States

Thesis Examination Committee:

Chairperson, William Sousa, Ph.D.

Committee Member, Tamara D. Madensen, Ph.D.

Committee Member, Emily I. Troshynski, Ph.D.

Graduate Faculty Representative, Jaewon Lim, Ph.D.