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The spatial demography of reported crime: an examination of urban-rural crime articulation and associated spatio-temporal diffusion processes, U.S. 1990 - 2000

Jeremy Reed Porter

THE SPATIAL DEMOGRAPHY OF REPORTED CRIME: AN EXAMINATION

OF URBAN-RURAL CRIME ARTICULATION AND ASSOCIATED

SPATIO-TEMPORAL DIFFUSION PROCESSES, U.S. 1990 – 2000

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Jeremy Reed Porter

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By

Jeremy Reed Porter

Approved:

Frank M. Howell
Professor of Sociology
(Director of Dissertation)
(Major Professor)

Lynn M. Hempel
Assistant Professor of Sociology
(Committee Member)

Emory P. Morrison
Assistant Professor of Sociology
(Committee Member)

Troy C. Blanchard
Associate Professor of Sociology
(Committee Member)

QiQi Lu
Assistant Professor of Statistics
(Committee Member)
(Minor Professor)

Xiahoe Xu
Graduate Coordinator Department of Sociology

Gary L. Myers
Dean of the College of Arts and Sciences

Name: Jeremy Reed Porter

Date of Degree: December 12th, 2008

Institution: Mississippi State University

Major Field: Sociology (Demography)

Major Professor: Dr. Frank M. Howell

Minor Field: Statistics

Minor Professor: Dr. QiQi Lu

Title of Study: THE SPATIAL DEMOGRAPHY OF REPORTED CRIME: AN EXAMINATION OF URBAN-RURAL CRIME ARTICULATION AND ASSOCIATED SPATIO-TEMPORAL DIFFUSION PROCESSES, U.S. 1990 - 2000

Pages in Study: 382

Candidate for Degree of Doctor of Philosophy

Recently, increased attention has been given to the social and environmental context in which crimes occur (Wells & Weisheit 2004). This new interest in the human ecology of crime is largely demographic, both in terms of subject matter and increasingly in terms of the analytic methods used. Building on existing literature on the social ecology of crime, this study introduces a new approach to studying sub-county geographies of reported crime using existing census place and county definitions coupled with spatial demographic methods. Spatially decomposing counties into Census places and what Esselstyn (1953)

earlier called "open country," or non-places, allows for the development of a unique but phenomenological meaningful sub-county geography that substantively holds meaning in conceptualizing rural and urban localities in the demographic analysis of crime. This decomposition allows for the examination of core-periphery relationships at the sub-county level, which are hypothesized to act similarly to those at the national level (Agnew 1993; Lightfoot and Martinez 1995). Using 1990 to 2000 Agency-level UCR data within this approach, I propose to use spatial statistics to describe and explain patterns of crime across differing localities. Potential processes of spatial mobility in regards to the spread of criminal activity from places to non-place localities are also examined.

In order to adequately understand these spatial patterns of crime while testing the usability of the new place-level geography, several of the generally accepted theories of crime and a number of explanatory factors and covariates are tested. Furthermore, using this sub-county geography, significant patterns of spatial diffusion and contagion are through the implementation and modification of the spatio-temporal model, which provides the current point of departure and put forth by Cohen and Tita (1999). The results are promising and suggest a meaningful contribution to the ecological analysis of crime and the larger sub-discipline of spatial demography.

DEDICATION

I would like to dedicate this final dissertation to all those who have supported and inspired me through my time at Mississippi State University. Chief among these individuals are my two daughters (Jamirah and Ciara), my partner (Susannah), my two brothers (Jason and David), and my mother (Linda). Thanks to you all, I couldn't have done it without you!

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TABLE OF CONTENTS

Page

DEDICATION ii

ACKNOWLEDGEMENTS........ iii

LIST OF TABLES........ vii

LIST OF FIGURES........ x

LIST OF EQUATIONS........ xv

CHAPTER

I. INTRODUCTION 1

Background. 1
Statement of Purpose........ 5
Objectives of the Study........ 9
Implications and Justification of Study........ 10

II. LITERATURE REVIEW........ 13

Organization of the Literature Review. 13
General Crime Trends. 16
Overview of Trends in Criminal Offending........ 16
Rural-Urban Crime Patterns........ 22
Explanations of Spatial Variation in Crime........ 33
Analyzing Crime in Space 45
Geography of Crime 45
Spatial Methodology and the Spatial Analysis of Crime 49
Contagion, Diffusion and the Mobility of Crime 51
Spatially-Centered Analytic Methodology 59
The Continued Linkage of Space and Crime 60

Theoretical Framework 65
Overview 65
Classical Economic Theories of Location 67
The Chicago School...71
Recent Trends in Location Theory...72
Human Ecology and Inter-Place Relations 76
Ecological Theories of Crime...78
Social Disorganization..83
Routine Activities Theory 86
Hypotheses..89
Hypotheses: Phase One - Description..90
Hypotheses: Phase Two - Explanation 91
Hypotheses: Phase Three - Spatio-Temporal Diffusion 92

III. METHODOLOGY 94

Sources of Data 94
Uniform Crime Reporting Program 95
Construction of Sub-County Geography and Data 98
Measurement and Operationalization 100
Dependent Variables 100
Data Processing for the Dependent Variable 101
Independent Variables 107
Data Processing for the Independent Variables 110
Analytic Techniques 112
Descriptive Analysis...114
Explanatory Analysis 116
Exploratory Analysis of Spatial Diffusion.......................................117
Model Specifications..120
Descriptive/ESDA Model Specifications 120
Explanatory Regression Model Specifications.................................129
Exploratory Analysis of Spatial Diffusion.......................................147

IV. DESCRIPTION OF REPORTED CRIME IN SUB-COUNTY GEOGRAPHIES 1990 - 2000 152

Statistical Description 152
Description and Distribution of Criminal Offending 154
Covariation among the Determinants of Criminal Offending 162
Spatial Description..166

Spatial Distribution of Raw Crime Rates....167
Locally Smoothed Type-Specific Crime Rates....171
Spatial Dependence in Criminal Offending....181
Mean Differences in Type-Specific Crime Rates....194
Spatio-Temporal Interactions and Heterogeneity....209
Statistical Trends in the Type-Specific Crime Rates....209
Spatial Trends in the Type-Specific Crime Rates....215
Conclusions....227

V. EXPLANATIONS OF REPORTED CRIME IN SUB-COUNTY GEOGRAPHIES, 1990 & 2000....230

Regression and Spatial Diagnostics....232
OLS Results Explaining Criminal Offending....234
Spatial Results Explaining Criminal Offending....236
Conclusions....268

VI. IDENTIFYING SPATIAL MOBILITY IN REPORTED CRIME THROUGH PLACE TO NON-PLACE DIFFUSION, 1990 – 2000....270

Identifying Within County Neighborhoods....271
Diffusion: Univariate versus Bivariate LISA Results....273
Geographic Distribution of Bivariate LISA Results....278
Identifying Counties with Significant Contagious Diffusion....284
Conclusions....295

VII. CONCLUSION....298

Summary of Findings....298
Discussion....307
Limitations....314
Implications and Future Research....316

BIBLIOGRAPHY....320

APPENDIX

A. ANCILARY TABLES AND FIGURES....340

ENDNOTES....379

LIST OF TABLES

Table Page

1 Variables of Interest for Place-Level Geographic Examination of Reported Criminal Offending.....108

2 Descriptive Statistics of Theoretically Appropriate Independent Variables.....159

3 Descriptive Statistics of Theoretically Appropriate Independent Variables by Geographic Identifier (Place vs. Non-Place).....160

4 Bivariate Correlation Between all Theoretically Appropriate Independent Variables, 1990.....164

5 Bivariate Correlation Between all Theoretically Appropriate Independent Variables, 2000.....165

6 Type-Specific Logged Crime Rates by Spatial Categorization 1990 – 2000.....195

7 Main and Interaction Effects of the Logged Type-Specific Crime Rates By Selected Classifier Variables.....196

8 Trends in Type-Specific Crime Rates by Place-Level Geography.....208

9 Mean Differences in Raw Change by Type-Specific Crime Rates Across U.S. Region, Metro Status, and Place-Level Geography.....210

10 Raw Rate Changes in Type-Specific Logged Crime Rates by Spatial Categorization.....214

Table Page

11 Crosstabulation of Spatial Clusters for Changes in Type-Specific Crime Rates by Place-Level 226

12 Spatial Regression Results of Logged Total Crime Rates on a Social Disorganization Theoretical Framework 239

13 Spatial Regression Results of Logged Property Crime Rates on a Social Disorganization Theoretical Framework 244

14 Spatial Regression Results of Logged Violent Crime Rates on a Social Disorganization Theoretical Framework 246

15 Spatial Regression Results of Logged Total Crime Rates on a Routine Activities Theoretical Framework 251

16 Spatial Regression Results of Logged Property Crime Rates on a Routine Activities Theoretical Framework 255

17 Spatial Regression Results of Logged Violent Crime Rates on a Routine Activities Theoretical Framework 258

18 Spatial Regression Results of Logged Total Crime Rates on an Integrated Ecological Theoretical Framework....261

19 Spatial Regression Results of Logged Property Crime Rates on an Integrated Ecological Theoretical Framework....264

20 Spatial Regression Results of Logged Violent Crime Rates on an Integrated Ecological Theoretical Framework....266

21 Crosstabulation of Univariate versus Bivariate LISA Classification of Type-Specific Crime for Each Locality, 1990 – 2000 276

22 Count and Percent of Counties by Type-Specific Crime Rate and Diffusion Trend, 1990 – 2000 283

Table Page

A.1 Mean Differences in Type-Specific Crime Rates Across U.S. Region, Metropolitan Status, Place-Level, and Temporal Period 341

A.2 OLS Regression Results of Logged Total Crime Rates on a Social Disorganization Theoretical Framework 342

A.3 OLS Regression Results of Logged Property Crime Rates on a Social Disorganization Theoretical Framework 343

A.4 OLS Regression Results of Logged Violent Crime Rates on a Social Disorganization Theoretical Framework 344

A.5 OLS Regression Results of Logged Total Crime Rates on a Routine Activities Theoretical Framework 345

A.6 OLS Regression Results of Logged Property Crime Rates on a Routine Activities Theoretical Framework 346

A.7 OLS Regression Results of Logged Violent Crime Rates on a Routine Activities Theoretical Framework 347

A.8 OLS Regression Results of Logged Total Crime Rates on an Integrated Ecological Theoretical Framework....348

A.9 OLS Regression Results of Logged Property Crime Rates on an Integrated Ecological Theoretical Framework....349

A.10 OLS Regression Results of Logged Violent Crime Rates on an Integrated Ecological Theoretical Framework....350

A.11 List of Counties with Identified Place to Non-Place Contagious Diffusion by State, Type-Specific Crime and Crime Trend, 1990 – 2000....351

LIST OF FIGURES

Figure Page

1 Place/Non-Place Territory Illustration, Golden Triangle Region, MS....6

2 U.S. Total Crime Reported, 1973 – 2005....19

3 Illustration of Local Indicator of Spatial Association, Golden Triangle Region, MS....61

4 Screenshot of Figure layout of ID Structure for Place/Non-Place Geography....102

5 Data Processing of Dependent Variables, 1990....104

6 Data Processing of Dependent Variables, 2000....105

7 Q-Q Plot for Normality of Dependent Variables, 1990....155

8 Q-Q Plot for Normality of Dependent Variables, 2000....156

9 Local Empirical Bayes Smoothed Logged Total Crime Rate, 1990....172

10 Local Empirical Bayes Smoothed Logged Property Crime Rate, 1990....173

11 Local Empirical Bayes Smoothed Logged Violent Crime Rate, 1990....174

12 Local Empirical Bayes Smoothed Logged Total Crime Rate, 2000....177

13 Local Empirical Bayes Smoothed Logged Property Crime Rate, 2000....178

Figure Page

14 Local Empirical Bayes Smoothed Logged Violent Crime Rate, 2000 179

15 Significant Spatial Clusters of Total Crime Rate, 1990 184

16 Significant Spatial Clusters of Property Crime Rate, 1990..........................185

17 Significant Spatial Clusters of Violent Crime Rate, 1990............................186

18 Significant Spatial Clusters of Total Crime Rate, 2000 190

19 Significant Spatial Clusters of Property Crime Rate, 2000..........................191

20 Significant Spatial Clusters of Violent Crime Rate, 2000............................192

21 Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Place-Level Using a Repeated Measures ANOVA Approach, 1990 – 2000..200

22 Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Metropolitan Status Using a Repeated Measures ANOVA Approach, 1990 – 2000 201

23 Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by U.S. Census Region Using a Repeated Measures ANOVA Approach, 1990 – 2000 202

24 Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Decade Using a Repeated Measures ANOVA Approach, 1990 – 2000..203

25 Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Place-Level and Metropolitan Status Using a Repeated Measures ANOVA Approach, 1990 – 2000 204

26 Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Place-Level and U.S. Census Region Using a Repeated Measures ANOVA 205

Figure Page

27 Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Place-Level and Decade Using a Repeated Measures ANOVA Approach, 1990 – 2000 206

28 Raw Change in the Logged Total Crime Rate per 100,000, 1990 – 2000....................216

29 Raw Change in the Logged Property Crime Rate per 100,000, 1990 – 2000....................217

30 Raw Change in the Logged Violent Crime Rate per 100,000, 1990 – 2000....................218

31 Significant Spatial Clusters in the Raw Change in the Total Crime Rate, 1990 – 2000....................221

32 Significant Spatial Clusters in the Raw Change in the Property Crime Rate, 1990 – 2000....................222

33 Significant Spatial Clusters in the Raw Change in the Violent Crime Rate, 1990 – 2000....................223

34 Bivariate LISA Results Showing Significant Spatial Clusters of Total Crime, 1990 – 2000 279

35 Bivariate LISA Results Showing Significant Spatial Clusters of Property Crime, 1990 – 2000....................280

36 Bivariate LISA Results Showing Significant Spatial Clusters of Violent Crime, 1990 – 2000....................281

37 Selected Example of Place to Non-Place Diffusion of High Criminal Offending, Total Crime, 1990 – 2000 287

38 Selected Example of Place to Non-Place Diffusion of High Criminal Offending, Property Crime, 1990 – 2000....................288

Figure Page

39 Selected Example of Place to Non-Place Diffusion of High Criminal Offending, Violent Crime, 1990 – 2000 289

40 Selected Example of Place to Non-Place Diffusion of Low Criminal Offending, Total Crime, 1990 – 2000 291

41 Selected Example of Place to Non-Place Diffusion of Low Criminal Offending, Property Crime, 1990 – 2000........292

42 Selected Example of Place to Non-Place Diffusion of Low Criminal Offending, Violent Crime, 1990 – 2000 293

43 U.S. Counties by Identified Patterns of Contagious Diffusion, 1990 – 2000........306

A.1 Logged Total Crime Rate per 100,000 Population, 1990........359

A.2 Logged Property Crime Rate per 100,000 Population, 1990 360

A.3 Logged Violent Crime Rate per 100,000 Population, 1990........361

A.4 Logged Total Crime Rate per 100,000 Population, 2000........362

A.5 Logged Property Crime Rate per 100,000 Population, 2000 363

A.6 Logged Violent Crime Rate per 100,000 Population, 2000........364

A.7 Parallel Coordinate Plots Identifying General Temporal Trends in the Logged Total Crime Rate, 1990 – 2000........365

A.8 Parallel Coordinate Plots Identifying General Temporal Trends in the Logged Property Crime Rate, 1990 – 2000 366

A.9 Parallel Coordinate Plots Identifying General Temporal Trends in the Logged Violent Crime Rate, 1990 – 2000........367

A.10 Boxplots Examining Mean Differences in Type-Specific Logged Crime Rate by Place-Level Geography, 1990 & 2000........368

Figure Page

A.11 Boxplots Examining Mean Differences in Type-Specific Logged Crime Rate by Metropolitan Status, 1990 & 2000 369

A.12 Boxplots Examining Mean Differences in Type-Specific Logged Crime Rate by U.S. Census Region, 1990 & 2000 370

A.13 Boxplots Examining Mean Differences in Type-Specific Logged Crime Rate by Temporal Period, 1990 & 2000 371

A.14 Boxplots Examining Mean Differences in the Logged Total Crime Rate by U.S. Region and Metropolitan Status, 1990....................................372

A.15 Boxplots Examining Mean Differences in the Logged Property Crime Rate by U.S. Region and Metropolitan Status, 1990....................................373

A.16 Boxplots Examining Mean Differences in the Logged Violent Crime Rate by U.S. Region and Metropolitan Status, 1990....................................374

A.17 Boxplots Examining Mean Differences in the Logged Total Crime Rate by U.S. Region and Metropolitan Status, 2000....................................375

A.18 Boxplots Examining Mean Differences in the Logged Property Crime Rate by U.S. Region and Metropolitan Status, 2000....................................376

A.19 Boxplots Examining Mean Differences in the Logged Violent Crime Rate by U.S. Region and Metropolitan Status, 2000....................................377

A.20 Example of Nearest Neighbor Definition for Spatial Weight Matrix Using Place-Level Centroids 378

LIST OF EQUATIONS

Equation Page

1 Computation of Non-Place Territory Data..98

2 Computation of Raw Crime Rate 121

3 Computation of Local Empirical Bayes Smoothed Crime Rate 123

4 Computation of Global Moran's I Coefficient 125

5 Regression Model: Social Disorganization/Urbanization Component 137

6 Regression Model: Social Disorganization/Racial-Ethnic Heterogeneity Component 137

7 Regression Model: Social Disorganization/Socioeconomic Status Component 138

8 Regression Model: Social Disorganization/Family Disruption Component 139

9 Regression Model: Social Disorganization/Fully Specified Model...........139

10 Regression Model: Social Disorganization/Fully Specified Model and Place-Level Interactions 140

11 Regression Model: Routine Activities/Suitable Target Component.........142

12 Regression Model: Routine Activities/Motivated Offender Component 142

Equation Page

13 Regression Model: Routine Activities/Lack of Capable Guardian Component 143

14 Regression Model: Routine Activities/Fully Specified Model 144

15 Regression Model: Routine Activities/Fully Specified Model Plus Place-Level Interactions 144

16 Regression Model: Integrated Social Disorganization and Routine Activities Model 146

17 Regression Model: Integrated Social Disorganization and Routine Activities Model Plus Place-Level Interactions 146

18 Computation of Global Bivariate Moran's I Coefficient 148

19 Computation of Bivariate Local Indicator of Spatial Association Coefficients....150

CHAPTER 1

INTRODUCTION

Background

Recently, increased attention has been given to the social and environmental context in which crimes occur, including a revival of theories concerning social disorganization and increased usage of crime mapping techniques (Wells & Weisheit 2004). However, most of the attention given to the ecological context of crime has focused primarily on only minute portions of the available geographical units of analysis. Furthermore, the extreme heterogeneity which exists in many of the geographies used for the examination of crime, such as counties (Land 1990; Messner and Anselin 2004; Messner et al. 1999), makes it evident that a better understanding of all ecologically distinct units is important in order to further our understanding of reported crime in general.

Often ecological studies of crime tend to only focus on urban settings while neglecting areas of a more rural or of less-developed urban character (Clinard 1942; Wells and Weisheit 2004). This oversight has therefore neglected to understand crime in the vast majority of place settlements in the U.S., as seventy-seven percent of all Census places are outside of urban areas and sixty percent are in places with a population of less than 2,500 people, the common Census definition of rural locality (Wells & Weisheit 2004). Furthermore, it is well known that place-level geography, as with most sub-county level geographies, vary qualitatively based on the metropolitan status of the county in which they are contained.

As evidence, it is important to note that rates of all FBI UCR index crimes are both qualitatively and quantitatively different in urban places when compared to rural places, suggesting that patterns, motivational factors, and types of crimes vary distinctly both within and between these localities (Glaeser & Sacerdaote 1999, Clinard 1942, Petee and Kowalski 1993, Wells & Weisheit 2004). Urban crime tends to concentrate in the downtown areas of cities because of high rates of unemployment and poverty, high concentrations of physical deterioration and as well as minority populations, and a larger proportion of youth (Ackerman 1998). In contrast, rural crime lacks this concentration and characterizes the offender as being extensively mobile, resulting in a detachment from any "home community" (Ackerman 1998). Nonetheless, while the current state of the literature is definitely urban-centric, it is not without notice by scholars of crime.

A half-century ago, Esselstyn (1953) called for the development of a "geographically non-urban" criminology. Esselstyn was primarily focused on the development of a conceptualized space, resulting in the development of the term "open country" used to describe any area not under some form of place-level police (and by inference, other city-based) jurisdiction. Since this early call for a better understanding of the geography of crime, which is included in the ecological analysis of crime, we must point out that there has been substantial discourse on the constitution of urban and rural, in relation to a number of demographically pertinent issues. Among these are how to include space into such analyses as well as the appropriate geography upon which to base these inquiries.

The demography of crime as a sub-discipline has adopted a number of demographic approaches to the study of the patterns, motivations, and spatial spread of crime. A county-level study on the structural covariates of crime by Land (1990) has led to the growing devotion of criminologists, demographers, and other social scientists of the spatial distribution of criminal violence (Baller et al. 2001, Anselin et al. 2000). Land (1990) pointed out that the general trend in most of the existing literature of that time used states as the primary unit of analysis, due to the fact that state-level data were readily available and often required less data management. However, other studies have argued that a more appropriate measure is the Metropolitan Area (MA) level, based upon the argument that MA's more readily represent community boundaries (Messner et al. 1999). On the other hand, this is further debated as the use of metro areas neglects substantial within-unit variability, often concerning both the structural covariates as well as the dependent variable of interest (usually crime) (Messner et al. 1999).

More recently, a number of articles have examined *between*-county variations in crime rates (Messner et al. 1999, 2005; Messner and Anselin 2004; Baller et al. 2001; Baller and Richardson 2002). However, there still exists a certain level of *within*-county variation and a lack of agreement on the community or neighborhood associated with a particular sub-county boundary (Cohen & Tita 1999, Baller et al. 2001, Messner et al. 1999, Anselin 2000, Hipp 2007). In regard to these works, there is the increasing use of GIS combined with spatial statistics. This general trend is a documented pattern throughout the social sciences (Goodchild and Janelle 2004). Figuring prominently among these issues is the specification of the optimal unit of analysis (Cohen & Tita 1999, Baller et al. 2001, Messner et al. 1999, Anselin 2000, Goodchild & Janelle 2004, Hipp 2007). Thus, it is important to add to what is known about more optimal geographies which will add to our understanding of the spatial demography of reported crime and its patterns of change. Results are promising concerning the future implications of sub-county geographies in the analysis of many non-criminological issues, such as the more traditional demographic subject of population dynamics (Howell et al. 2008).

Statement of Purpose

Following recent trends in the literature, this study introduces a new approach to understanding rural and urban sub-county geographies using existing Census place definitions. The use of places in conjunction with areas not within an incorporated or Census Designated place, Esseltyn's "open country" (or *non*-places), allows for the development of a sub-county geography that substantively holds meaning for conceptualizing rural and urban in the demographic analysis of crime; that is, whether the locality is inside of a legally-recognized place or "out in the county". Figure 1 is an illustrated example of the place/non-place territory geography in the Golden Triangle Area of Eastern Mississippi, a non-metropolitan area. Within the figure one can see that each county is made up of a series of places and a non-place. In Oktibbeha County the primary place is Starkville and the balance of the county is then referred to as the non-place[1]. This sub-county geography will be used to designate the units of analysis in the proposed study.

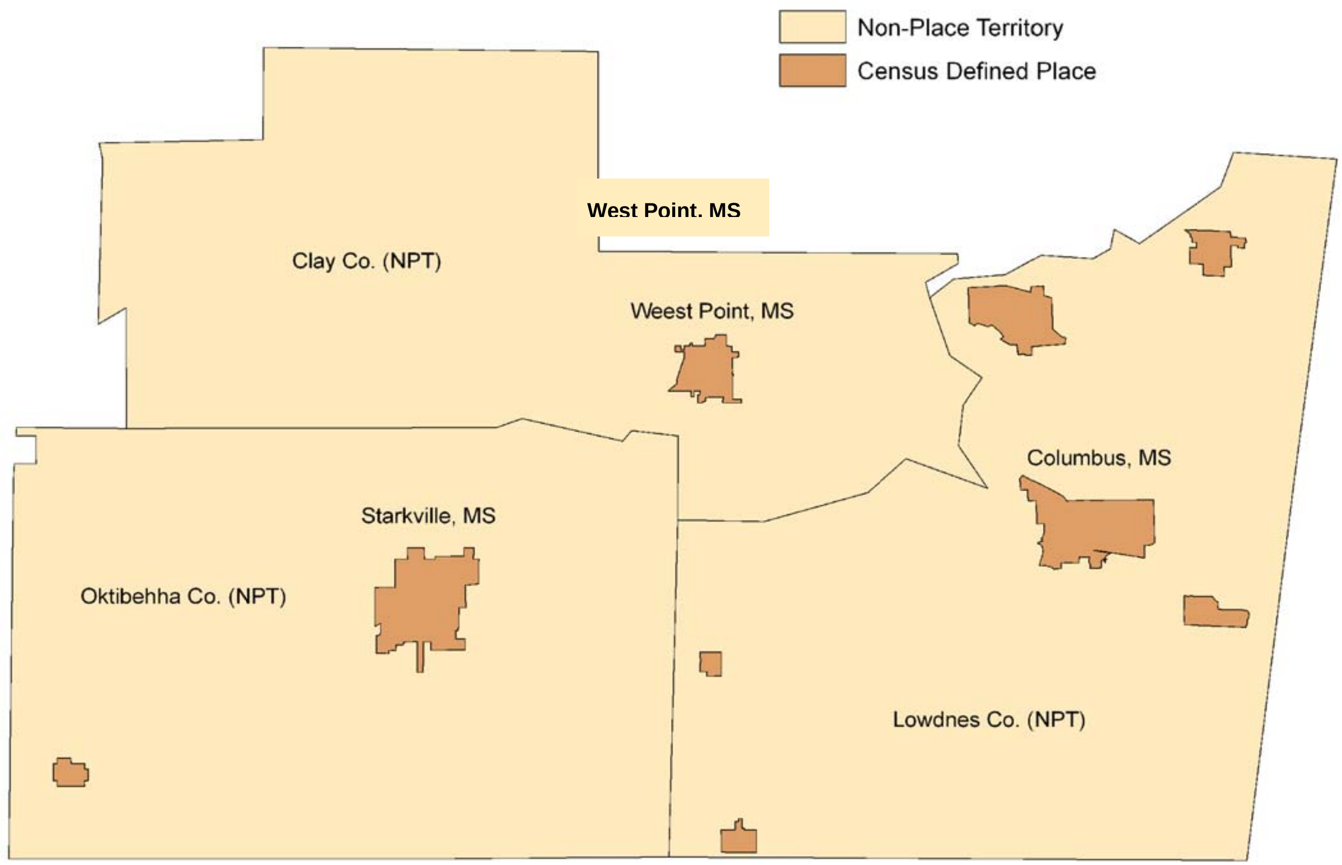


Figure 1. Place/Non-Place Territory Illustration, Golden Triangle Region, MS

Furthermore, the use of exploratory and explanatory spatial analysis techniques allow for the examination of an inherently spatial phenomena of concern in this study, the differing patterns of urban and rural crime and the diffusion processes of urban crime to nearby rural localities. Within this explanatory examination, arguably the two most prominent ecological theories of criminal offending will be examined, independently and in an integrated form. The ecological theories used in this dissertation are the structurally centered social disorganization Theory and the more agency-oriented routine activities theory.

The final portion is interested in modeling the mobility of crime associated with the fluidity of criminal behaviors between areas based on their place-level classification; places or non-place territories. The mobility of criminal offending is examined via the implementation of analytic techniques associated with the identification of diffusion patterns among the spatial movement of social processes and behaviors. Of the two primary types of diffusion, contagion and hierarchical (Cohen and Tita, 1999), this process of diffusion involves contagious diffusion due to the contiguous nature of the units of analysis and the core-periphery relationship associated with the inherent 'downward' transmission of ideas, behaviors, and social processes between core places and periphery non-place territory (Agnew 1993; Lightfoot and Martinez 2005).

Contagious diffusion refers to the movement of phenomena through direct contact by neighboring entities, as is the physical relationship between places and there adjacent, and often surrounding, non-place counterparts. Two main types of contagious diffusion, according to Cohen and Tita, are *relocation* diffusion and *expansion* diffusion. *Relocation* diffusion involves to movement of a phenomena form a "seed" location to a contiguous neighbor. Within the field of criminology this is often referred to as "displacement" (Paulsen and Robinson 2004). Whereas, e*xpansion* diffusion refers to the outward spread of a phenomenon from a central "seed" location, which is much more associated with the economic view of the spread of innovation, fads, and trends (Smelsner 1963).

The entire dissertation takes a spatial approach to this examination, as there are a number of inherently spatial processes identified and introduced in the following literature review associated with the act of criminal offending. Using a spatially centered approach is important for both statistical and substantive reasons (Baller et al. 2001; Anselin 1995). Statistically, neglecting to use a spatial approach to examine phenomena in which spatial process operate may lead to biased, inaccurate, and unreliable results (Anselin 2000, Baller et al. 2001). The implementation of a spatial approach allows for the implicit control of spatial autocorrelation concerning both the variable of interest and the structural level determinants. This is explained in greater detail in the literature review and methodology sections. Spatially, causal processes may not work evenly across space and the use of spatial analyses can help to identify those areas where theses processes differ (Baller et al. 2001). Therefore, it is important to examine the variation in criminal offending and determinants of such behavior on a national scale but at a sub-county unit of analysis.

Objectives of the Study

This study would build upon a number of recent studies involving the analysis of the covariates of crime, while also implementing new spatial analyses techniques focused on the diffusion patterns of differing types of crime. Recent literature points out that it is imperative to understand this spread of crime to small communities, in hopes of better understanding the patterns and processes of both the diffusion of crime and the patterns and processes of crime in non-urban areas, which usually gets overlooked in favor of crime processes in more urban areas (Ackerman 1998; Esseltyn 1953).

Furthermore, this spatial demography of crime hopes to identify and explain these differences using traditional and accepted methods of statistical analysis, while also introducing new and exploratory spatial methods. Within this framework, the proposed study will concentrate primarily on the examination of independent variables shown to be substantively important in the following chapters of literature review. Lastly, the proposed study will extend the creative and resourceful work on the spatial diffusion of crime by Cohen and Tita (1999) by using multivariate spatial statistics (involving static LISA results; see Anselin 1995) for the two separate time periods of 1990 and 2000.

The method will examine the spatial mobility of crime from core-city areas to periphery-hinterland areas based on an integrative approach to a couple of spatially centered theoretical frameworks. This process implements the Tita and Cohen (1999) method of detecting diffusion of spatial/temporal processes, grounded in the contagious nature of outward diffusion identified by concentric zonal model and the core-periphery relationships between places and non-places (Agnew 1993; Park et al. 1925; Lightfoot and Martinez 1995; Alber et al. 1971).

Implications and Justification of Study

The proposed project has a number of important implications for the spatial demography of crime and beyond. First and foremost, the successful implementation and completion of this project could provide a potentially rich and new resource for the examination and understanding of criminological processes at the sub-county level. Full national-scale (continental) data sets for two decennial periods (1990, 2000) with the associated sub-county geographies would yield significant research potential beyond this dissertation work.

Furthermore, as noted above, this project could hold a great deal of promise for a better understanding of the proper unit of analysis for the understanding of criminological processes. This point is primarily based on the fact that the creation of this new geography is theoretically-driven based on the definitions of Census places and the substantive meaning individuals give to city limit boundaries and the outer localities. This new geography can be utilized for studies of demographic processes far outside the demography of reported crime (i.e. diffusion of population, suburbanization).

Lastly, this project will be one the first to introduce the use of new spatial clustering techniques as a way of identifying patterns of crime mobility in a specified temporal period. Again, this mobility will be examined under the guise and implementation of diffusion techniques most commonly associated with the movement of new trends, fads, ideas, and social processes to new geographic areas for introduction. Up to this point early attempts at tracking diffusion geographically have built a good 'jumping off point' from which this dissertation hopes to extend the current methodological techniques. Most recently, Cohen and Tita (1999) have implemented the use of the univariate LISA (Local Indicator of Spatial Association) statistic at different time periods as a crude measure of diffusion. This project will introduce the use of the bivariate form of the same statistic in an attempt to uncover the same processes but with a joint test for statistical significance. In summary, this project is interested in the implementation and testing of the new place-level geography, both as a general 'container' or crime and as a substantively meaningful geography in which to measure the mobility of reported criminal offending.

CHAPTER II

LITERATURE REVIEW

Organization of the Literature Review

The literature review in the following chapter is organized around several topics relevant for the proposed study and ultimately culminating in a set of testable research hypotheses. The literature review is organized around explicitly reviewing independent content concerning the various components of this dissertation project. In sum, the sections associated with the literature review will overview the primary substantive issue of criminological offending, overview the advancement of literature and methods in related examinations of the intersection of crime, space and time, and introduce a theoretical framework.

The first section in the Literature Review Chapter is an overview of some key trends in crime and some of its major covariates. This is important to lay out in the beginning of this review in order to identify current trends and determinants of crime useful in the later development and specification of testable hypotheses and related explanatory statistical models. A strand of this literature includes a more detailed examination of urban and rural crime trends, including their similarities and differentials. Again, it is important to note the rural/urban specific trends and the potential relationships between the two as the final phase of the analysis is aimed at understanding the spatial mobility of crime from 1990 – 2000 across and between these classifications.

Furthermore, this first section aims to identify and explain the processes and implications of spatial variation in criminal offending. This section takes particular interest in the differentials in rural and urban offending, while also underscoring the similarities that exist between the two. On this point, urban crime is often associated with the density of the population, decay of infrastructure, suitable targets, and formality in criminal prosecution (Ackerman 1998; Wilson 1991). While rural crime is often overlooked and dealt with in a much more informal manner (Schmidt 1960a, 1960b; Esselstyn 1953). However, it is important to note that while these differences are more the norm than not, there exists a noticeable amount of similarities in the models used to predict criminal offending across both classifications.

A second topic in this review of the literature is an examination of the current state of the spatial analyses of crime, concerned with the documentation of various approaches and findings from existing research associated with such methodology. This section is warranted as this dissertation hopes to build upon existing arguments through the introduction of a new mid-level geography, which is one of the primary contributions of this dissertation project. While it is important to understand the theoretical arguments pertaining to the development of this new geography, most of the writing on the processing and development of this geography will take place in the Methodology section.

Finally, the last section of the review is concerned with the development of a guiding theoretical framework, including both and examination of pertinent criminological theory and a general theory of space and location. While this dissertation is methodologically and substantively demographic in nature, it is undeniably criminological, simply based on the dependent variables (total, property, and violent crime), and therefore a review of appropriate theoretical frameworks from the sub-field of criminology is warranted. This review will only focus on a further subset labeled ecological theories within the field of criminology, which includes the structurally grounded social disorganization Theory and the more agency based routine activities theory. These sets of theory directly link the act of criminal offending to the larger ecological context in which the individual action takes place (Paulsen and Robinson 2004).

Furthermore, due to the high priority placed on the spatial distribution of criminal offending, non-random behavior processes, theories directly related to space and location will be directly examined. This portion of the theoretical framework will include an in-depth examination of spatial theory in general and its relationship to methods of spatial mobility and diffusion. This is deemed to be both appropriate and necessary as location theory, in general, posits a number of testable hypotheses associated with the spread of behavioral processes such as criminological behavior. This review will aim to introduce the development of spatial/location theory, human ecology, and criminological related ecological theories in order to identify important points and issues concerned with the current project at hand.

Ultimately, the review concludes with a set of testable research hypotheses grounded in the literature. The model specifications to test such hypotheses will be introduced later at the end of the subsequent Methodology chapter.

General Crime Trends

Overview of Trends in Criminal Offending

Crime has been a significant concern in the United States throughout most of its history. There have seen considerable fluctuations in crime rates over the past quarter-century (See Figure 2). However, crime in the United States has remained relatively stable since 2000 and rates for some types of crimes have even declined. The Bureau of Justice Statistics (BJS) reports that over the last decade, serious violent crime levels, including homicide, rape, robbery, assault, and so forth, have continually declined (BJS 2007). Rates of property crime, violent crime (for both males and females) and firearm-related crime (with a slight increase in 2005) have also been in decline *at a national level*.

However, the Bureau of Justice Statistics also reports that the reporting of crime, arrests, and convictions have steadily increased over the past decade (BJS 2007). Indeed, as the percentage of crimes reported to policing agencies has been increasing, the proportion of those convicted in Federal court and sentenced to prison has been increasing. Not surprisingly, due largely to the revival of the "War on Drugs" during the Regan administration, of cases concluded in Federal district court since 1989, drug cases have increased at the highest rate.

Also on the rise are the number of adults being convicted of felonies and the number of those felons being sentenced to prison or jail. Over two-thirds of the felons convicted in State courts in the U.S. were sentenced to prison or jail (BJS 2007). As a result, the number of adults in the correctional system has also been increasing and, of those being convicted, over half of the increase in the state prison population since 1995 is due to an increase in prisoners that have been convicted of violent offenses. However, after sharp increases in the 1980s and 1990s, the incarceration rate has more recently grown at a slower pace.

In 2005, the number of those within the prison population sentenced to death increased for the fifth consecutive year. However, in 2006, there were seven fewer executions than there were in 2005. Although most of those in prison are minorities, since the Supreme Court reinstated the death penalty in 1976, more than half of those sentenced to death have been white. Within state prisons and jails, however, suicide and homicide rates have been declining but this coincides with an increase in direct expenditures for each of the major criminal justice functions. While this information reports on the overall crime trends in the United States as a nation, crimes and criminal activity vary both geographically as well as demographically. This is true for both national and international trends.

Internationally, trends in crime show wide variations in the size of place and rate of growth with crime rates. For example, according to Brennan-Galvin (2004), two of the largest metropolitan areas in the world, Tokyo and Shanghai, are consistently among the safest cities in the world. On the other hand, recent trends in a number of Latin American cities points to homicide rates which are significantly related to both city size and urban population growth. Other factors such as population density and age structure were also found to be important predictors (Brennan-Galvin 2004).

Currently within the United States, however, Ackerman (1998) reports that small cities with a population under 100,000 are experiencing increases in the violent crime rate of 67.5% and the property crime rate of 12.9%. Violent

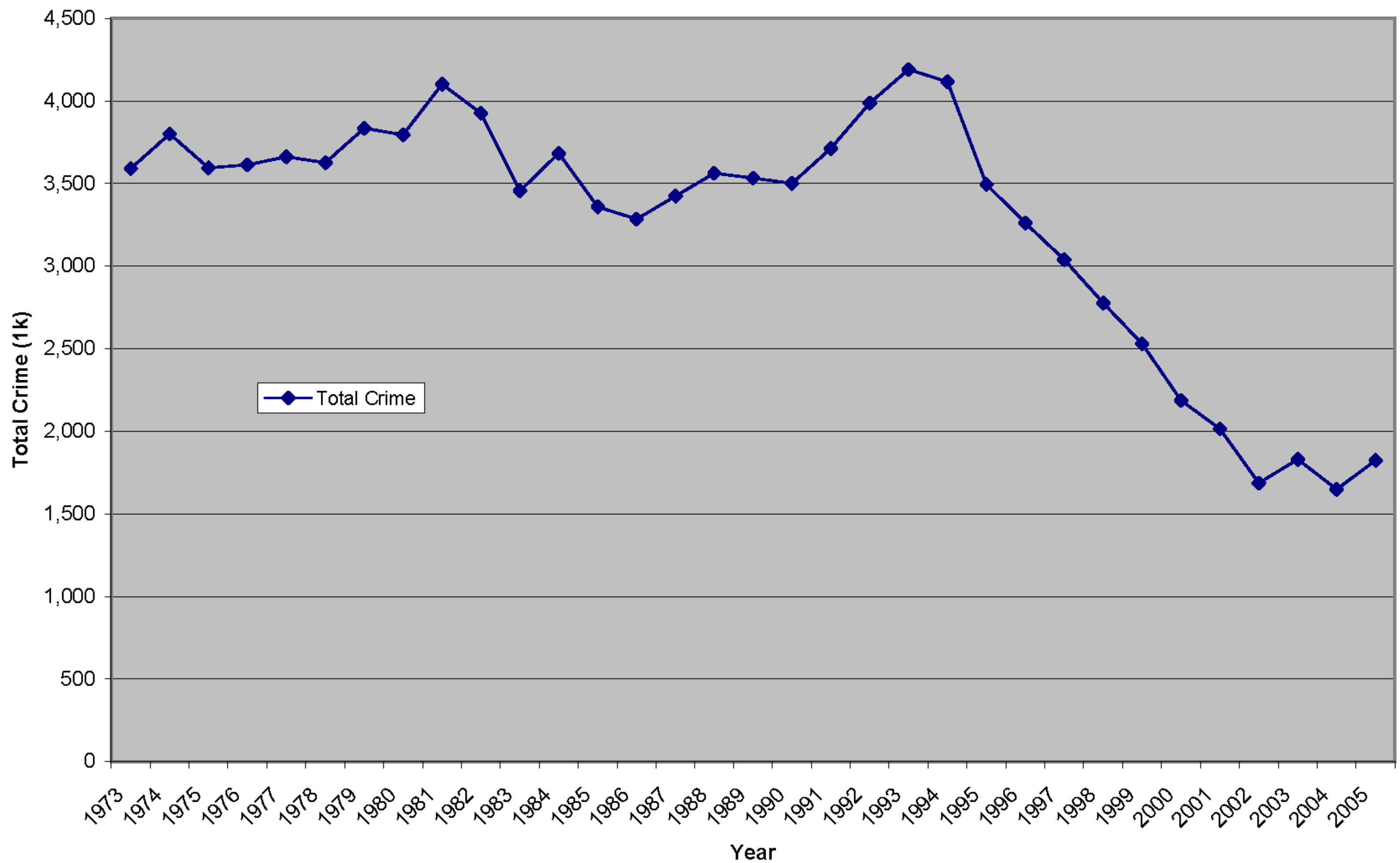


Figure 2. U.S. Total Crime Reported, 1973 – 2005

crimes include murder, robbery, assault, and rape, while property crimes include burglary, larceny, and auto theft. During the 1980's, this increase was especially dramatic as these smaller cities experienced crime rate increases at a faster rate than medium sized cities (100,000 – 500,000) and large cities (> 500,000) (Ackerman 1998).

Researchers suggest that the U.S. is seen as an anomaly among westernized countries due to large increases in crime over the past thirty years. These include increases in violent crime from 860 per 100,000 in 1969 to 1,218 per 100,000 in 1998, a rise in fear of crime indicators from 31% of people expressing hesitancy to walk alone at night to 41% in 1998, and the fact that individuals in U.S. cities are over twenty times more likely to have a firearm than residents of cities in the U.K. (Body-Gendrot 2001). These national increases in crime rates, however, are not a new development. According to the President's Commission on Law Enforcement and Administration of Justice, the crime rate was rising faster in the late sixties than the population (Beasley & Antunes 1974). However, more recent reports suggest that crime rates in the United States, especially violent crime rates, have started to stabilize and in some cases even decline (BJS 2007).

Within the United States, researchers have reported that there are also consistent regional variations in crime rates by the type of crimes being committed. Paulson and Robinson (2000), for example, found that, as of 2000, the highest rate of serious property crime occurred in the South, while the highest rates of violent crime occurred in the West. Other types of non-violent crime, however, are much less prevalent in the South, relative to other regions. Within those groups, high variability exists as the highest rates of murder and assault were found in the South in 2000 (Paulson & Robinson 2004: ch.2). Within the United States, however, homicide trends have consistently been variable across the entire U.S., although they have been consistently higher in the South region that the rest of the country (Paulson & Robinson 2004: ch.2).

In order to fully understand the variations in crime by place, it is also important to understand how crime rates are reported and calculated. Crime *rates* are most commonly reported as the number of reported crimes per 100,000 residents of the population. The crime rate usually consists of index crimes per 100,000 residents. The results are computed either as a total group of reported crimes or broken down by specific index crimes (Grogger & Willis 2000). Using this conventional method, Grogger and Willis (2000) found that the introduction of crack cocaine drove Metropolitan Area crime rates up ten percent, in the early 1980s, compared to the national averages.

Some problems with the use of these crime rates involve either small levels of occurrence of crime or of a small population base at-risk for victimization or reporting (Waller and Gotway 2005; Bailey and Gatrell 1995; Anselin 2002). Small numbers that produce unreliable and highly variable estimates can be improved upon via the introduction of a Bayesian statistical approach, in which the statistical estimation is supplemented by prior knowledge about the parameters of interest (Bailey and Gatrell 1995). For instance, in a spatial analysis of cancer risk and prevention, a risk estimate was deemed to be unstable because the variation did not follow the variation in population, meaning that a high rate did not necessarily mean a high risk (Anselin 2006). In order to adjust for this issue Anselin (2006) borrowed "prior" information on rates in order to smooth the current rates used in his analysis. Other approaches involve the use of Poisson based regression modeling techniques in order to examine the actual counts of rare events, such as crime, as opposed to the conversion of those events to rates (Osgood 2000; Osgood and Chambers 2000). In this study, a spatial regression approach will be implemented in order to test the utility of the place-level geography on two of the best established ecological theories of criminal offending.

Rural-Urban Crime Patterns

The preceding review has introduced some of the most basic points concerning criminal offending and the academic study of such behaviors. This section of the review will build on these basic tenants by examining of the relationship between criminal offending and rural vs. urban classification. Furthermore, this section is concerned with the identification of both the urban and rural determinants of crime, while taking into account the importance of ecological space, which is an inherent component of rural/urban differences in criminal offending.

City life has almost always been associated with higher crime rates. This was recognized by even some of the earliest sociologists such as Emile Durkheim and Max Weber (Crutchfield 2007). However, while there is and has been "general consensus among criminologists that urban areas have higher rates of crime than rural areas, not all cities or neighborhoods experience similar levels of crime and violence; there is widespread variation in crime levels across urban spaces" (Crutchfield 2007: 77). A number of contributing factors have been explored to identify the source of this variation and include things such as poverty, poor living conditions, high levels of disruption, high concentrations of minorities, population density, city size, and so forth.

Contemporary criminologists continue to focus their attention on the trends in and the determinants of both urban and rural crime in the hopes of contributing to the extensive literature that has been devoted to this well-debated research topic. It is important to note that the operational delineation of urban and of rural often falls on the metropolitan status of the unit of analysis (i.e. county). However, recent studies in the examination of criminological processes have begun to address the observation that counties tend to be less homogeneous, in terms of rural and urban characteristics, than they are treated through the simple assignment of metropolitan status. The following review on urban and rural crime reports on a number of research findings, many of which directly identify rural and urban crime rates as being synonymous with metropolitan and non-metropolitan crime rates.

For example, Ackerman (2001) suggests that high crime tends to concentrate in the downtown area of cities because of high rates of unemployment and poverty, high concentrations of physical deterioration and minorities, and a larger proportion of youth. Due to the distance decay effect, the concentrations of these structural covariates create a higher crime rate in the inner city, which continually decreases as one moves away from the downtown area (Ackerman 1998). Similarly, Mandenka and Hill (1976) found that for personal crimes, there are consistently strong relationships between the crime rate and poverty, population density, and the percent black.

Wilson (1983), however, purports that urban crime is, along with many of the ills that face the inner city, often viewed as largely a problem of race. Wilson argues that, instead of problems of race and racial discrimination plaguing these areas, it is the products of previous discrimination that perpetuates the problems of the inner city today. In seeking a solution, Wilson suggests that it is the high rates of unemployment and the increasingly shrinking pool of marriageable men (due to unemployment, high mortality and incarceration rates) in these areas that should be confronted, not race per se. The suggestion of a relationship between poverty and urban crime has been long-standing, yet not uncontested.

As mentioned above, numerous other aggregate studies have empirically supported the existence of this relationship (Crutchfield 2007). However, other researchers such as Messner and Anselin (2004), Messner et al. (1999) and Blau and Blau (1982) have challenged this conception and found that the "areas with high populations of poverty do not necessarily have corresponding higher rates of violent crime" (Crutchfield 2007). They, like Wilson, point to the consequences of living in underclass neighborhoods that are characterized by isolation and a high concentration of poverty (Crutchfield 2007). The research on the link between race and urban crime has had more consistent findings of a strong positive relationship between racial composition and criminal violence (Crutchfield 2007). These, however, are certainly not the only suggested correlates of urban crime.

Many researchers have suggested that crime is associated with city size and population density and, as mentioned previously, these findings which support this theory. Brennan-Galvin (2004) believes that as the world continues to urbanize, there seems to be an impending problem with the increasingly strong relationship between city size, growth rate, and crime rates. Previously, however, Spector (1975) found that neither population density nor unemployment significantly affected the rates of urban crime. On the other hand, in contrast to earlier work by Spector (1975), Danzinger (1976) finds that both unemployment and population density are significantly influential in terms of predicting urban crime rates.

It is important to recognize that urban crime not only affects high-crime areas but can negatively impact the areas around them as well. Burnham et al. (2004) found that the effects of central city crime directly impact the economic health of suburbs but that effect is more negative the closer the suburb is to the central city. The authors also found that violent crime tends to have the greatest effect with a significant degree of distance decay evident.

Similarly, Schmid (1960a) examined the significant economic, demographic, and social determinants of urban crime. The author used a principal components approach to reduce the vectors of data, which ultimately identified eight factors. The factors measure low family status, low occupational status, low economic status, population mobility, low mobility groups, and race. Schmidt followed up earlier work (1960b), resulting in the major hypothesis that the spatial distribution of crime in urban locales follows natural areas, a concept developed originally by Park and Burgess of the Chicago School, and these distributions can be readily analyzed via gradient maps and isopleths.

In 1965, Boggs published a study on urban crime and pointed out that indicators of the occurrence of crime depend on a couple of factors with two being of extreme import. First, the familiarity of one with their victims is important based on the types of crime that occur in high crime areas. Often these types of crime include homicide, rape, robbery, and residential burglary. Secondly, profitability is important in the types of crime that occur in high-rank social neighborhoods. These crimes are usually less violent in nature and include auto theft, business burglary, other non-residential day and night burglary, and grand larceny (Boggs 1965). However, urban areas are not the only places that cope with criminal activity and its consequences.

When one thinks of rural areas, one usually does not think of high crime rates. Most often one thinks of small towns, farming, and friendly people. However, reported crime statistics tell us otherwise. In fact, according to the National Center on Rural Justice and Crime Prevention (NRJCP), the falling crime rate has benefited urban and suburban areas more than rural areas (NRJCR 2007). However, due to the sheer magnitude of criminal offending in more urban areas, it is important to note that they had further to fall. Because urban areas are thought to have the majority of reported crime, researchers have tended to focus their efforts on studying crime patterns in urban areas. As a result, research on rural crime is much sparser and much less conclusive. According to Esselstyn (1953), rural crime is neglected in the field of criminology. He called for the development of the term "open country" to describe any area not under some form of place-level police jurisdiction. An "open country" crime would be any crime in which an "open country" officer must take action. Historically, the most consistent and well-known "open country" officers are those affiliated with the county's local sheriff. In "open country," the sheriff is seen as symbolizing local control over local problems and is often given power to handle crime, and what they deem to be crime, in any way they see fit (Esselstyn 1953). His half-century old call for significant research on rural crime largely went unheeded with the exception of work by a very few rural-centric researcher (Donnermeyer and Barclay 2005; Donnermeyer et al 2006; Donnermeyer 2007).

Previously, Bloch (1949) also suggested that very little had been done on studying crimes and criminals in areas labeled or defined as being of rural character. In fact, according to Bloch, most criminology solely focused on the urban offender. Results at the time suggested that economic depression induced criminal activity, controlling a number of other socioeconomic covariates (Bloch 1949). Preceding this earlier work, Clinard (1944) also felt that rural crime offenders were, to a great extent, neglected in criminal research. In an attempt to understand the criminal behavior of the rural offender, in relation to the more generally understood urban offender, he did an analysis of sixty Iowan inmates from the "open country." He characterized rural offenders as being extensively mobile, resulting in a detachment from any "home community" and thus leading to irresponsible patterns of criminal activity (Clinard 1944). Other research on crime in the "hinterlands" found that improvements in record keeping of reported crimes and arrest is the driving force between the "crime-wave" in the early 1970's (Gibbons 1976). Also, makeshift record keeping techniques in many rural sheriffs office, suggest that the primary purpose of the position of many rural crime figures (i.e. sheriff) is for the purpose of peacekeeping as opposed to the purpose of punishing those who break the law (Gibbons 1976).

As evident in this literature, there are a number of differences between urban and rural crime patterns. Exploring these differences in more detail, the National Center on Rural Justice and Crime Prevention (NCRJCP 2007) found that the majority of arrestees in rural (non-metropolitan) counties were white (79%). Rural violent crime victims were also less likely to be victimized by a stranger and the most common place to be victimized in a rural area is one's home, compared to the street or public transportation in urban and suburban areas.

Furthermore, rural offenders had extensive contacts outside of their home communities and exhibited more mobility, in terms of frequency of moves, than non-offenders, resulting in a relative detachment from any locality they would consider to be home (Clinard 1942). Rural offenders, on average, also participated in fewer community organizations but were increasingly likely to be involved in a network of criminal relationships as urbanization increased.

Among urban offenders, participation in gangs was prevalent. As a result, urban offenders much more readily took on the persona of the "criminal social type," while this was largely non-existent in the rural offenders and minimally existent in offenders from areas of low to moderate urbanization. The criminal social type is characterized by criminal techniques, criminal argot, and a progressive criminal life history. Rural offenders, on the other hand, did not regard their actions as crimes or themselves as criminals. Overall, crime patterns suggest that the influence of urban areas and the detachment of offenders from personal relationships drive the development of the "criminal social type" (Durkheim 1893; 1895).

Clinard (1942) further found that there are quantitative differences in the incidence of crime in areas based on the degree of urbanization. Similarly, Glaeser and Sacerdote (1999) reported that crime rates tend to be higher in large cities when compared to small cities and rural areas. In 1994, metropolitan areas reported seventy-nine percent more crime than smaller-sized American cities and three hundred percent more than rural areas. Recent findings suggest that the relationship between city size and crime rate can be primarily explained by the presence of more female-headed households in cities and that higher financial returns explained about one-quarter of the variation and a lower likelihood of arrest account for about one-fifth of the variation. His conclusions were that urban crime is higher for three basic categories: 1) higher financial returns to criminal activity in urban areas, 2) lower probability of arrest in urban areas, and 3) urban areas tend to attract crime-prone individuals (Glaser and Sacerdote 1999).

Some half century later, Paulson and Robinson (2004 (ch.2)) also observed that urban areas have consistently had higher crime rates than rural areas, with urban and rural rates of violent crime much larger in discrepancy than that of urban and rural property crimes. These pattern areas to be linear as suburban areas have also consistently had higher rates of crime than rural areas, but lower than urban areas (see Glaeser and Sacerdaote 1999).

In an attempt to explain these differences, Petee and Kowalski (1993) suggested that historical differences in rural and urban crime have disappeared with the modern standardization of education and advances in transportation and telecommunications. Wells and Weisheit (2004) further suggested that the earliest developments in American criminology focused a great deal on the ecological context in which the crime occurred. In recent years, a return to these foci has developed with increased attention again being given to the social and environmental context in which crimes occur, including a revival of theories concerning social disorganization and increased usage of crime mapping techniques. However, as evidenced by much of the preceding literature in this review, most of the attention given to the ecological context of crime has focused primarily on urban settings, while neglecting to areas of a more rural character.

This oversight has neglected to understand crime in a majority of localities in the U.S., as seventy-seven percent of all places are outside of "urban" areas and sixty percent are in places with a population of less than 2,500 people (Wells and Weisheit 2004). While, it is important to note that rates of all index crimes were higher in urban places when compared to rural places, this ultimately leads to the interpretation that patterns, motivational factors, and types of crimes vary distinctly both within and between these areas. The research findings further suggest a lack of homogeneity within the units of analysis often used to assign urban and rural geographies. This implicit homogeneity assumption hinders the maturation of our understanding of crime and it ecological context.

Explanations of Spatial Variation in Crime

Why do some localities have higher or lower crime than others? This is a central question in the areas of criminology and other crime-related fields and attempts to address this issue have been undertaken by a number of researchers. However, while there is some agreement on a number of issues concerned with its examination, there is far from a general consensus. As a result, the range of methods and resulting explanations are often as variable as the subject matter itself. This section aims to identify many of the issues and research methods while also focusing on the primary covariates used in each of the studies reviewed.

Researchers examining ecological crime variations have used a wide variety of methods and predictors. For example, in 1949, Bloch used a case study approach to analyze change in crime across selected rural communities using a number of covariates, including the sex ratio, size of place and change in size of place, age differentials over time, education, religion, parent mortality, marital status, employment status, previous convictions, and the types of offenses. Petee and Kowalski (1993) used a social disorganization framework, within a cross-sectional design, to examine crime differentials, which included percent poverty, residential mobility, racial heterogeneity, population density, and percent single-parent households.

Wells and Weisheit (2004), on the other hand, explored the possible indicators of urban crime and, in doing so, computed two sets of factors, one measuring an ecological framework and another a social structural framework. The ecological framework consisted of five factors including urban density, housing instability, family instability, population change, and economic change. The urban density factor consisted of persons per square mile and the proportion of people within urban places. The housing instability factor consisted of the percent of housing units renter occupied, proportion of households that are family (vs. non-family), and percent of housing units without municipal sewer. The family instability factor consists of the proportion of single-parent households and the divorce rate, while the population change factor consisted of change in overall population size and the proportion of the population that has moved in the last five years. The final factor in the ecological framework is the economic change factor, which consists of recent changes in median household income level and recent changes in the proportion of the population living under the poverty line (Wells and Weisheit 2004).

Within the social structural framework there were three factors: economic resources, racial heterogeneity, and cultural capital. The economic resources factor consists of median household income, proportion of persons living below poverty, and the proportion of adults with at least a high school education. The racial heterogeneity factor consists of proportion of the population non-white and the degree of overall racial/ethnic diversity. Lastly, the cultural capital factor consists of the proportion of the population that is Hispanic, the proportion of the population foreign-born, and the proportion of the population living in non-English speaking households. There are two additional variables, the proportion of the population between 15-24 and the employment rate of the community (Wells and Weisheit 2004).

Differentials in methods and predictors have also led to similar differences in findings. Historically, a significant amount of research on crime has been dedicated to distinguishing the primary covariates of crime. In doing so, there has been a significant amount of debate regarding what those primary covariates should be. Several social characteristics including race, gender, class, education, single-parent households, population density, etc. have been linked to differentials in criminal activity. For example, Moses (1947) equated contiguous areas in Baltimore based on social characteristics in order to test the hypothesis that racial differences in crime rates were, in fact, the product of not controlling for differences in socioeconomic status. His findings suggest that there are similarities in the patterns of offenses between blacks and whites overall, although blacks were more concentrated in crimes consisting of the loss of life (Moses 1947). These findings further suggested that much of the racial variation explaining involvement in criminal offending could be further accounted for by socioeconomic differences.

More recently, Paulson and Robinson (2004) found that some of the most consistent covariates of crime include variables associated with social disorganization and include poverty, residential mobility, immigration, racial/ethnic heterogeneity, population density, single-parent households, and collective efficacy (Paulson and Robinson 2004 (ch.3)). They found significant demographic differences on the perception of crime based on race, gender, age, education, tenure, and location of residence within the community. They also found a distance decay effect, in which crime rates as one moves from the "seed" location of highest crime (Paulson and Robinson 2004 (ch.5)).

A lot of this variation is a result of the demographic differences across place both within urban areas or between urban and rural areas. Chilton (1964) compared covariates of crime across three metro areas, Baltimore, Detroit, and Indianapolis, and found that the use of factor analysis yielded similar factors in each case. These findings would suggest a consistent pattern of crime across place in relation to urban metropolitan crime.

Some researchers interested in the examination of urban crime, however, have produced complementary results. Danzinger (1976), for instance, found that both population density and unemployment were significant predictors of crime which was in contrast to some of the previous literature purporting that the two were insignificant. According to Wilson (1983), the percent black in an area is often a significant predictor of urban crime. Although Wilson also points out that this is less of a race problem and more of a structural inequality problem, primarily based on income discrepancies between blacks and whites. Similarly, Krivo & Peterson (1996) reported that the most consistent predictor of crime rates is the degree of poverty in the area. Grogger and Willis (2000) found that the introduction of crack cocaine drove Metropolitan Area crime rates up ten percent compared to the national averages in the early 1980s. It is important to note, however, that the areas with the highest rates of crack-cocaine use tend to have the highest percentage of blacks and the highest rates of poverty. These relationships have yet to be successfully dissected.

Despite the consistent finding that there is a positive relationship between unemployment rate and population density and the rate of crime in an area, there are still some inconsistencies. Kvalseth (1977) compared some of these conflicting findings in the literature and suggested that the decomposition of crimes by type and the decomposition of unemployment rate by gender yielded somewhat conclusive findings. First, the total urban unemployment rate has a positive influence on the rates of burglary and larceny. Second, the male unemployment rate has a positive influence on robbery. Lastly, total unemployment rate has a positive influence on the incidence level of rape (Kvalseth 1977).

As pointed out above, rural as well as urban crime is both quantitatively and qualitatively different and often the methodology and covariates of choice reflect that difference. Indeed, it has been widely suggested that city size is a significant predictor of crime and the belief has been that crime is more prevalent in large cities as opposed to smaller cities. "According to the 1994 Statistical Abstract of the United States, metropolitan areas have 79% more violent crimes than other American cities and 300% more violence than rural areas. New York and Los Angeles have crime rates that are approximately four times higher than the crime rates of metropolitan areas as a whole and have violent crime rates that are more than 2.5 times the violent crime rates of all metropolitan areas." (Glaeser and Sacerdote 1999: 225). Similarly, as of 2005, the Bureau of Justice Statistics reports that over half of all homicides occur in cities with a population of 100,000 or more and almost one-quarter of the homicides occurred in cities with a population of over 1 million.

In order to explain the connection between higher crime rates for large cities and urban areas when compared to smaller cities and rural areas, Glaeser & Sacerdote (1999) decomposed the effect of city size on crime into three components: 1) higher financial returns to criminal activity in urban areas, 2) lower probability of arrest in urban areas, and 3) urban areas attract crime-prone individuals. Other important covariates of crime in their study included population size, percent population below poverty, percent of owner-occupied housing, percent non-white, percent with four years of high school, percent with four years of college, unemployment rate, percent female-headed households, and region. Their findings suggest that higher pecuniary benefits in large cities, lower probabilities of arrest and recognition in urban areas and the greater presence of female-headed households in cities can all explain, at least in part, the large city-crime connection (Glaeser and Sacerdote 1999).

While a large literature exists on crime in large cities, there is little known of crime in smaller areas, especially on the evolution or patterns of crime in those smaller areas (Ackerman 1998). It has been suggested by some researchers, however, that the rate of *increase* in crime in these smaller areas is much faster when compared to the larger and medium sized areas. Indeed, according to Ackerman (1998), small cities (cities of less than 100,000 people), are experiencing the largest rate of growth in crime, especially for violent crime. Ackerman (1998) found that poverty, along with its related conditions, tends to be one of the primary correlates of violence. A factor analysis of potential covariates yielded two factors from the original set of variables. Factor one consisted of low housing value, unemployment, poverty, youth, and poorly educated individuals.

Factor two consisted of the percentage of blacks in the population, the percentage of female-headed households, and older housing. Using exploratory spatial data analysis to examine distribution of homicides and principal components factor analysis to account for multicolinearity in the predictors, Messner et al. (1999) found evidence that in addition to more affluent areas, rural or agricultural areas served as barriers against the diffusion of homicides. This is one of the few studies of crime to use spatial regression models, albeit at the county-level. These rural vs. urban differentials will be explored in more detail in the following sections.

As can be seen from this review, there is a considerable amount of debate within the criminal literature as to an explanation of the variations in criminal activity as well as the methods to determine those explanations. According to Baller et al. (2001), much of the apparent inconsistency in the literature concerning different findings on the covariates of crime can be explained with the problem of multicolinearity in traditional structural predictors. To avoid these issues many have created composite measures via the principal components method of data reduction. For example, Beasley & Antunes (1974) reviewed early uses of factor analysis and pointed out that, without further examination, factor analysis is simply a data reduction tool and should not be used for exploratory purposes. However, simply as a process of preliminary analysis, the bivariate correlations reveal important correlates of crime, which can be reduced to three types; 1) measures of socioeconomic status, 2) measures of crowding, and 3) measures of ethnic or subculture segregation (Beasley & Antunes (1974).

On the other hand, Land et al. (1990) point out that the existing literature on the determinants of homicide rates is unreliable due to heterogeneity, primarily the result of different time periods, units of analysis, sampling techniques, and various problems concerning statistical analysis. In their approach, principle components analysis was used to address problems of multicolinearity among a number of the covariates of homicide rates across time and space. The authors purport that this method was used to simplify the dimensionality in structural covariate space.

The results suggest the existence of two clusters of variables, a population component and a resource-deprivation and affluence component. The population structure component consists of county population size and population density, while the resource-deprivation and affluence component consists of median family income, the percent of families living below poverty, the gini index of family income inequality, the percentage of the unit of analysis that is black, and the percentage ages under eighteen not living with both parents (Land et al. 1990). Included in the analysis as controls were the percent divorced, percent ages 15-29, the unemployment rate, and a dummy for if the unit of analysis was in the Census defined south or not. Findings suggest that the resource deprivation and affluence component has the largest effect on homicide rates, with a slightly larger influence at the city level compared to the state level (Land et al. 1990). Thus, the Land et al. study suggests that some influences may be stronger at smaller area geographies.

Some more contemporary research has suggested an association between lead exposure and the frequency of crime and delinquency (Stretesky and Lynch 2004). For example, Nevin (2000) showed a consistent pattern associated with the increased exposure to lead and reduction in IQ. This finding is important as a link between IQ level and criminal behavior was also found (Nevin 2000). Indeed, in the past 70 years, exposure to lead has been directly related to rates of criminal activity (Nevin 2000). Similarly, Needleman et al. (1996) reported that medical researchers believe that as much as 20% of all crime is lead-associated leading to the conclusion that those individuals living in areas with high concentrations of lead "may be exposed to environmental conditions that possess the potential to stimulate aggressive behaviors such as crime and delinquency" (Stretesky and Lynch 2004: 214).

Building upon these ecological determinants of criminal offending, another strand of literature has been concerned with the effect of the "strength of policing" on crime rates (Chamlin 1989; Brandl et al. 1995; Narayan and Smyth 2006). Most of this literature is interested in the strength of policing as measured by the number of either police officers or the number of employees on the police agencies payroll. However, there is also great interest in the reductive effects associated with the size of the police force (Narayan and Smyth 2006). For instance, is there more crime reported because there are a greater number of police officers to make arrests or is the greater number of police officers actually deterring criminal activity (Brandl et al. 1995). Conversely, are there a greater number of police officers on the streets because there is more crime (Brandl et al. 1995)?

In either case, the strength of the police force can directly affect the criminological processes of interest. That is especially the case when examining the possible effect of the policing on the mobility of crime. Perhaps most directly, the influence of increased policing on high crime areas may drive crime to another area. This process of crime displacement may take the form of contagious or hierarchical diffusion (Paulson and Robinson 2004). The former is the most likely via the spread of crime to contiguous neighboring areas that may be less likely to have the same police presence.

This model of the effect of police strength on the mobility of criminological processes is driven by the ecological context in which the change in the police force takes place. In fact, some researchers have found significant effects of socio-structural variables on the size of the police force while some research has found them to be completely independent when compared to the size of the police force at previous time periods (Brandl et al. 1995). In support of the argument that Chamlin (1989) found that there were specifically three such structural variables that significantly affects the size and change in the police force from 1972-1982. She identified it as being positively related to a rise in the level of property crime, higher levels of the percent black in the community, and higher levels of residential segregation.

Finally, Brandl et al. (1995) also point out that any effect of structural variables is often seen as spurious due to the fact that often all employees of the agency are lumped together, which creates a type of aggregation bias. It is, however, evident that the explanatory variables associated with the patterns and mobility of criminological processes vary widely by theoretical framework, but may in fact vary in more in terms of their importance and relevance across space. As the Land et al. (1990) results suggest, these effects could indeed be stronger when the unit of analysis is specified. While their results utilized much larger units of geography (state vs. city) than our sub-county units, they do hint at the distinct potential.

Analyzing Crime in Space

Geography of Crime

Crime comes in many forms and varies based on a number of factors and, as we have seen in this review, one major but understudied factor is place. However, as the previous section has suggested, the current examination of crime has been modified to accompany changes in the way in which processes are affected and spread and reorganized through space. In fact, now there is a great deal of concern on the actual diffusion process through which crime is spread, as there is evidence of a contagious model, which would support the early concentric zonal models of location theory, and a hierarchical model, which tends to support more of an spatial unorganized postmodern model of location theory (both are explained in greater detail in the following sections) (Park et al. 1925; Dear 1988; Dear and Flusty 1998). However, that is not to say that hierarchical models of diffusion are not organized, they just tend to follow social patterns as opposed to geographic patterns.

In either case, the unit of analysis as represented by the level of geography plays an important role in being able to understand crime, where it happens and why it might be happening in those places. However, the "proper" unit of analysis for this examination has been extensively debated. Messner et al. (1999) found that there are a number of geographies that could possibly be used for both the statistical and spatial analysis of crime, including metro areas, states, counties, cities, tract, and blocks. According to Messner et al. (1999), the selection of geography ultimately should rely on proper investigation of the phenomenon or process of investigation.

Messner et al.'s argument follows a much larger issue, which has received a large amount of attention in the field of geography. That is issue is the ability to select the correct unit of analysis or geography based on what has been called the Modifiable Aerial Unit Problem (MAUP) (Boldstadt 2006). MAUP is interested in the idea that smaller units of analysis do not necessarily constitute the communities they are designed to and in the same vein larger units of analysis tend to dilute variation between units[2]. In essence, MAUP makes the point that relationships between aggregate variables can vary widely, including changes in sign, but the choice of unit for the analysis must be distinguished by theory and empirical analysis.

The Messner et al. analysis used county level geography because it is a common unit of measurement for data collection, represents a complete range of social landscapes, and follows a precedent in the literature of using counties as unit of analysis. However, they acknowledged the importance of substantive sub-county spatial investigations of crime and the diffusion of crimes for a number of reasons. Most importantly, the idea that the vast social landscape within counties dilutes the possible ecological predictors of crime diffusion and masks possible diffusion processes at lower levels of geography. Their results suggest that findings vary significantly across different levels of ecological units (Messner et al. 1999).

Messner et al.'s thesis is far from new. Esselstyn (1953) was interested in creating a substantively meaningful geography for studying rural crime. Through this process he developed the term "open country" to describe any area not under some form of place level police jurisdiction. An "open country" crime would be any crime in which an "open country" officer (i.e. sheriff) must take action. This conceptualization is applicable to the current place vs. non-place dichotomy used in this study (explained further in the methods section), in which the portions of a county are decomposed to either be part of a Census defined place or part of the non-incorporated "non-place" territory.

There has historically been a slow transition towards smaller geographies (Cohen and Tita 1999). Land et al. (1990) pointed out that the trend in most of the existing literature at the time was to use states as the primary unit of analysis, due to the fact that data is readily available and often requires less in the file-building phase of the project. However, other studies have argued that a more appropriate measure is at the Metro Area (MA) level, because MA's more readily represent community boundaries.

Since the early 1990s, the use of smaller geographies as units of analysis has accelerated and has in some cases caused concern over the potential cross-cutting of neighborhoods, due to units of analysis that may be too small (i.e. block-level examinations). Krivo and Peterson (1996) use Census tracts in their analysis because of previous usage, but acknowledged that census tracts do not necessarily represent socially defined ecological neighborhoods. Baller et al. (2001), on the other hand, use counties as the unit of analysis, which they acknowledged might raise a form of the ecological fallacy problem (Robinson 1950). They argue, however, that the selection of the correct unit of analysis should be driven by theoretical consideration in conjunction with the ability to obtain data a certain levels of geography.

Due to the interest in this project of more phenomenologically meaningful rural-urban geographies), this study hopes to make use of the conceptually and substantively meaningful geography put forth by Esseltyn (1953), the "open country." The use of places and all "open country," or non-places, allows for the development of a sub-county geography that substantively holds meaning to most individuals in terms of where they live. In fact, with few exceptions, most individuals know whether or not they live in the city, township, place or "out in the county." This, however, is not the case with many of the other geographies used in the existing literature such as metro or non-metro counties. It is also not always the case with the examination of crime at the tract level due to the fact that the entire U.S. was only tracted as of 1990 and they hold little substantive meaning to the vast majority of the individuals in the U.S. Arguably, the place vs. non-place territory dichotomy gives the most efficient use of size and meaning in that it is substantively more meaningful than tracts yet allows for theoretically diluting the heterogeneity in the units of analysis as compared to counties.

Spatial Methodology and the Spatial Analysis of Crime

The continued advancement in desktop computing has fostered a tremendous increase in the availability and usage of Geographic Information Systems (GIS). The increased use of GIS and remote sensing in the social sciences (e.g. Goodchild and Janelle 2004) has allowed for the development of high-quality images as a way of displaying a multitude of information in spatial terms. It is however important to note that cartographic images themselves are not always the proper tool for the presentation of information. However, in the correct situation, they offer a valuable and powerful manifestation of information in conjunction with a research problem involving an inherent spatial element.

Craiglia et al. (2000) point out two areas that have benefited significantly from the implementation of GIS and spatial analysis tools are epidemiology and criminology, especially police services. These two areas are especially unique because of their high position on many political agendas and ever-increasing demand. In 1996 the National Institute of Justice allocated $15 million for the establishment of the Crime Mapping Research Center with the primary agenda of promoting and developing the use of crime mapping as an analytic tool for the better understanding of the ecological context and spatial distribution of crime (Craiglia et al. 2000).

Some of the earliest studies to focus on the concentration of crime in distinct types of communities were undertaken by French social ecologists interested in explaining the relationship between crime levels and varying social conditions of the resident populations across space (Guerry 1833a, 1833b; Quetelet 1833, 1842). While the methodology was no doubt crude, these studies laid the ground work for many of the ecologically-centered examinations of crime that have been undertaken over the span of about 175 years since those earliest studies.

In more recent times, Sampson & Morenoff (2004) examined homicide in Chicago neighborhoods through the study of spatial embeddedness, internal structural characteristics, and social organizational processes. The spatial proximity to violence, along with neighborhood inequality measures, was the most consistent predictors. Findings show rather large spatial effects resulting from models controlling for spatial dependence. Overall, the results of much of the spatial analyses of crime literature take aim at understanding and presenting the biasness associated with the use of more traditional techniques that do not take geographic proximity into account. One of the more interesting developments to arise from these analyses include the continued expansion of techniques for the measurement and identification of spatio-temporal patterns associated with the mobility of criminal offending patterns.

Contagion, Diffusion and the Mobility of Crime

Previously, Katz et al. (1963) pointed out that, sociologically, the processes involved in diffusion include: (1) acceptance, (2) over time, (3) of some specific item (idea or practice), (4) by individuals, groups, or other adopting units, (5) linked through specific channels of communication, (6) social structure, and (7) to a given value system or culture (Katz 1963). Using Katz et al.'s (1963) characterization of diffusion, Bowden (1970) points out that there are theoretically several factors that may affect the rate of adoption. First, personality differences, due to heredity, childhood upbringing, and adult experience affect one's predisposition to accept new ideas. Second, differing degrees of exposure to influences from outside the community, primarily through the media, promote the likelihood of the adoption of new ideas. Third, the amount of contact with individuals in the local community, especially those that are seen as sources of innovation, may directly impact one's likelihood of adopting new ideas (see also Glaser and Strauss 1964).

Similarly, Tita & Cohen (2004) measured the spatial diffusion of shots fired across city neighborhoods in Pittsburgh using E911 records. They find patterns that suggest positive spatial correlation and diffusion processes. Hierarchical diffusion seems to be at work as the authors find evidence that homicide rates grew initially across spatially independent, yet socially similar, areas. In later periods they found that the diffusion process became contagious in nature as the spread of shots fired moved in a spatially dependent pattern (Tita & Cohen 2004).

Within the examination of crime, the terms contagion and diffusion refers to different processes by which criminological phenomena spread. Diffusion refers to the actual process of movement while contagion refers to the mechanism of the diffusion process (Cohen and Tita 1999; Tolnay 1995; Tolnay et al. 1996; Akers 1997; Messner et. al 1999). Contagious diffusion, then, refers to the movement of phenomena through direct contact by neighboring entities. This explicitly calls for a contiguous nature of interaction between the two areas of interest between which the diffusion process is taking place.

Two main types of contagious diffusion, according to Cohen and Tita, are relocation diffusion and expansion diffusion. Relocation diffusion involves to movement of a phenomena form a "seed" location to a contiguous neighbor. Expansion diffusion refers to the outward spread of a phenomenon from a central "seed" location. Crime displacement may be a good example of relocation diffusion, as effective policing may push criminal activity out of one area and into an adjacent area. However, in the case of expansion diffusion the spread of crime is accompanied by a continued high level in the central "seed" area, commonly this is the traditional model for the "spread of crime" (Cohen and Tita 1999).

The second mechanism in which phenomena move is through hierarchical diffusion. This involves the process of transmission through an ordered sequence of classes or places. This type of diffusion is often typified by the spread of innovations from larger metropolitan areas to remote more rural areas. Hierarchical diffusion also occurs in one of two ways, through spontaneous innovation and imitation. Spontaneous innovation often occurs when there is the introduction of a widely accessible product available to all. Imitation occurs as a spread of ideas and practice between areas that are similar life-style and structural conditions. An example may be the spread of gang violence between large non-contiguous cities in the U.S. as a product of media coverage of the problem (Cohen and Tita 1999).

Within the study of diffusion, according to Messner et al. (1999), there are a number of crucial components, including the locations of both the source and the potential adopters of the process. The contiguous nature of diffusion between neighbors suggests a contagious model of diffusion, while a non-contiguous diffusion refers to the diffusion process through other mediums, such as relatively similar social and economic conditions. In either case, the process of diffusion may either take the form of adoptive diffusion or the diffusion through the process of displacement. Adoptive diffusion has to do with the spread of phenomena through the active acceptance at the local area of interest while remaining strong at the source. A displacement process of diffusion implies more of a movement of phenomena from one area to another, reviewed above the spread of criminological processes based on the presence or strength of "policing".

Akers et al. (1997) used survey data on adolescent drinking and drug behaviors to test the strength of social learning theory as a possible explanatory tool for the diffusion of ideas. Findings suggest that social learning theory is in fact an adequate tool and that the best component of the theory within this analysis is the role of imitation as a medium for the diffusion of behaviors. These findings suggest the medium through which hierarchical diffusion takes place is the modern telecommunications devices used in everyday life. These media allow for the diffusion of trends, ideas, and other forms of culture to be communicated from a remote point to others for the possible adoption of these phenomena through imitation.

Jones and Jones (2000) examined evidence of both developmental and contagion theories of crime. Developmental theory is concerned with the learned and genetically predisposed personality traits that eventually lead to the development of criminal behavior. Contagion theory, on the other hand, advances the idea the criminal activity is a process that spreads through processes of diffusion, either through the expansion or displacement of current crime patterns. The authors present evidence of both as possible explanations but also calls for the continued development of methodology to continue to advance these lines of thinking (Jones and Jones 2000).

Many people have used diffusion models to examine crime. Berkowitz and Macaulay (1971) presented the idea of hierarchical diffusion of criminal behavior through the intense coverage of specific crimes and the copycat crimes that follow. Of interest in their study is the assassination of John F. Kennedy and the unusual increase in the number of violent crimes that followed. The authors point out that they cannot exclude the fact that record-keeping procedures also improved during the time period even though non-violent crimes did not see the same unusual increase.

Later, Land et al. (1991) used a spatial diffusion model to understand the effect of religious pluralism and church membership at the county level. Other researchers have examined homicide data, looking for the diffusion of youth gangs across space. During peak years of growth in total homicides, contagious diffusion was apparent between neighboring census tracts. However, during non-peak years (general event) the increases in youth-gang homicides happen in non-contiguous tracts in a hierarchical matter.

Akers et al. (1997) found that the process of imitation among teenagers is a significant source of diffusion of behaviors. Messner et al. (2001) also used spatial diffusion techniques to examine lethal violence in the St. Louis area, using block-level data, over two periods of time, one of relatively stable homicide rates (1984-1988) and one of increasing homicide rates (1988-1993). They found that areas with affluent characteristics and areas rural in nature tend to block contagious diffusion, ultimately resulting in a hierarchical pattern of diffusion between non-contiguous counties (Messner et al. 1999).

Ackerman (1998) examined the spread of crime to small communities, in hopes of better understanding the patterns and processes of both the spread of crime and the patterns and processes of crime in smaller cities, using data from the UCR concerning twenty-three cities in Ohio. The sample of cities included the three largest cities (Columbus, Cleveland, and Cincinnati), three mid-sized cities (Akron, Dayton, and Toledo), and seventeen small cities. The results showed that crime was increasing fastest in cities between 40,000 and 100,000 in population size, and the distribution of crime, spatially, tends to follow the same patterns as in larger cities by its high spatial relationship to areas of undesirable socioeconomic characteristics. Relevant to this analysis, this would suggest that places within metropolitan counties should have higher crime rates as they meet both criteria, higher populations and areas of lower socioeconomic status.

In terms of displacement, Barnes (1995) pointed out that there are six potential types of displacement; temporal, spatial, target, tactical, perpetrator, and type of crime. In some cases these may overlap. For instance, in this analysis we expect the movement of crime from one place to another to be associated with both the temporal period (1990 – 2000), the spatial classification (place to non-place), and the type of crime (total crime versus property crime versus violent crime). The combinations of these processes are expected to create unique patterns of type-specific crime mobility, in some cases resulting in displacement, as opposed to contagious expansion.

Badurek (2007) used GIS to model the spatial displacement of crime and points out that there are two major problems that have traditionally accompanied the examination of crime displacement. These issues include how to identify types of displacement and how to analyze these displacements once they are identified. This project is directly interested in the contagious diffusion processes of within urban, place-to-place, crime diffusion and urban to rural, place to non-place crime diffusion. However due to the contiguous nature of the units of analysis involved in the theoretical movement of crime from urban to rural areas, this project is also interested in the type of movement from between these units of analysis, be it adoptive diffusion or displacement. Lastly, in the case of displacement the type of process of movement will be examined by the type of crime as pointed out as one of the six types of displacement by Barnes (1995), through total crime, violent crime, and property crime.

For illustration purposes only, Figure 3 shows what possible results from a spatial diffusion model may in fact look like when using the place vs. non-place territory geographies. Using the LISA approach of Anselin (1995) the "high-high" score in the West Point (place)/Clay County (non-place) area suggests that West Point had a high crime rate at T_1 and it is surrounded by areas that also had a high crime rate at T_2; in this case, Clay County, the non-place territory area. This can be interpreted to suggest contagious diffusion from one urban area to its surrounding rural areas. However, the other two places of interest, Starkville and Columbus, are shown to have a relatively high crime rate while the surrounding county (NPT) has a much lower crime rate in T_2. This would be evidence of a *lack* of adoption by surrounding areas, suggesting a lack of active contagious diffusion.

Spatially-Centered Analytic Methodology

It is important to understand the data needs for a given project to appropriately implement the resources available in a GIS, this includes the appropriate level of geography. The use of a sub-optimal level can lead to inaccurate findings and incorrect inferences about the data for the theoretical issues at hand. As merely one of many examples in the literature, compare the discussions in Anselin and Cho (2002a, b) and King (2002). One issue that arises when working with aggregate level geographies is the modifiable aerial unit problem (MAUP), which entails the dilution of variation at lower levels of geography due to the presentation of aggregate data.

In the social sciences, it is often not feasible to search for over-arching absolute truths in relation to many issues and phenomena as the residuals of imperfect models almost always show geographic patterns (Goodchild & Janelle 2004). Recently, a number of spatial techniques have been developed to help account for these inconsistencies across space. For example, Stewart Fotheringham developed geographically weighted regression, which supposes a linear model to be fit over units of analysis within a specified geographic area. The results produce a number of regression runs equal to N number of specified geographic areas. Also Luc Anselin, through his work in the development of Geoda, had developed local measures of association (i.e. his LISA statistic). Many scholars have increasingly used a variety of these techniques for their research concerning phenomena, which have been shown to be theoretically linked to space.

The increasing use of these methods has further pushed the development and understanding in relation to use of such methodologies and tools. In relation to this examination, and due to high degrees of spatial autocorrelation; "Spatial Analysis is statistically and substantively important for macro-level criminological inquiry" (Baller et al. 2001: 561). If spatial processes occur and are not accounted for the resulting estimates may yield inaccurate data from which inferences are made. Additionally, by assuming invariance across space you neglect to understand the fact that theses processes do not act identically across the geographic landscape (Baller et al. 2001).

The Continued Linkage of Space and Crime

All of these works illustrate the high potential of using spatially centered methods on the study of crime (which can easily be transferred to a number of

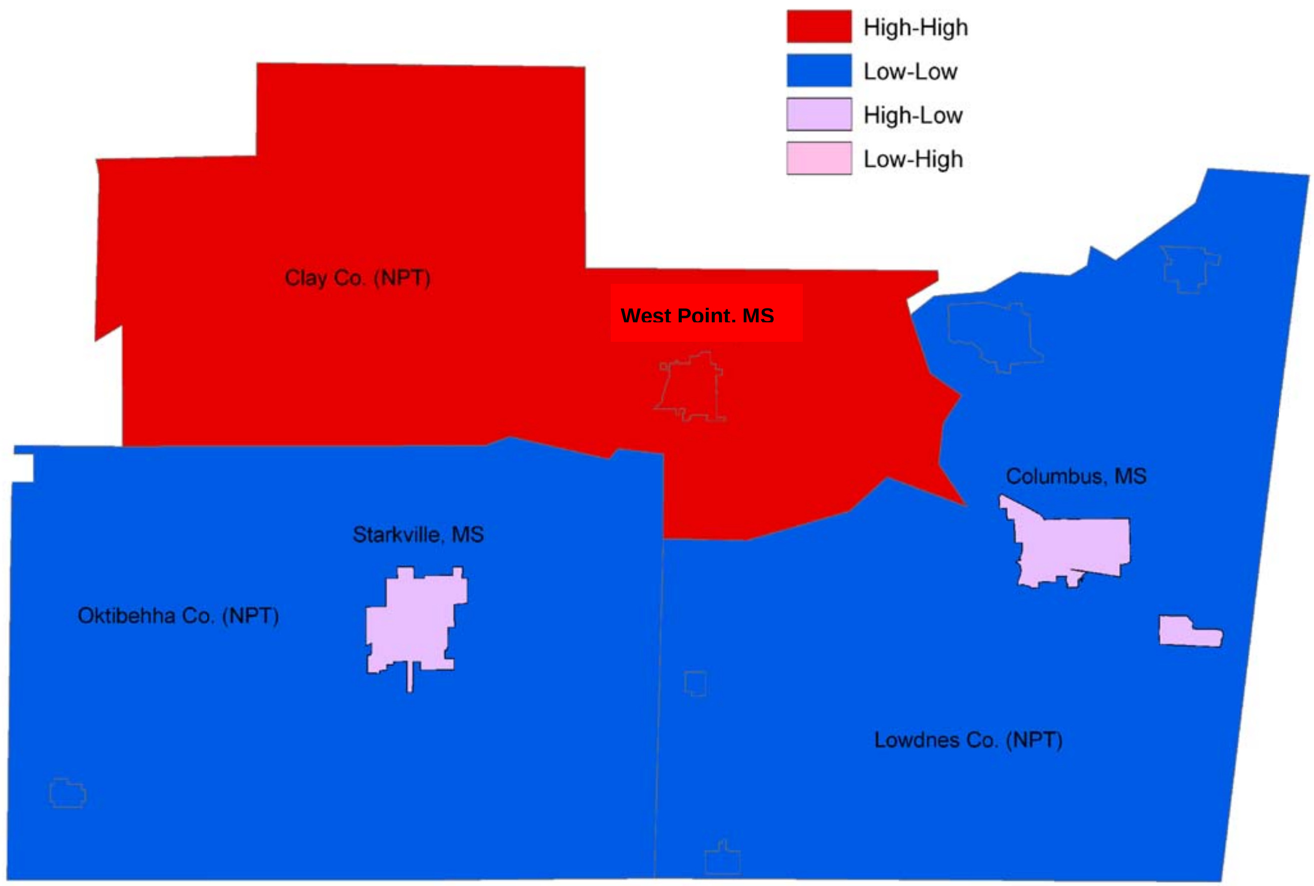


Figure 3. Illustration of Local Indicator of Spatial Association, Golden Triangle Region, MS

other phenomena). Furthermore, each has contributed to the development and maintenance of spatial theory, which finds its beginning, implicitly, in some of the more mainstream traditional theoretical frameworks, including some of the earliest work by the Chicago School (Park et al. 1925), select classical sociologists (i.e. Simmel's urban personality), the early rural sociologist at Wisconsin (Galpin 1915), and a number of other examples.

Early on in the history of American Sociology, Park et al. (1925) argued that in order to understand social life one must take into account the specific the social times and places in which they occur. Recently, there has been growing interest in the places in which crime occurs, both for the sake of better understanding the ecology of crime and for the ability to apply knowledge to the reduction of crime where applicable. Furthermore, recent advances in technology have increased the ease and practicality of such analyses.

The ability to computerize and apply spatial statistics to the mapping of crime is a relatively new phenomenon, developing during the early 1990's (Anselin et al. 2000). According to Anselin et al. (1999b), statisticians have long been aware of potential effects of violations of basic regression assumptions, but spatial techniques did not disseminate into practice until recently, primarily due to technological hurdles.

Currently, one of the most popular methods for the measure of spatial dependence is the Local Indicator of Spatial Autocorrelation (LISA) statistic. The LISA statistic is visualized using a scatterplot of the variable of interest's score plotted against the mean score of all spatial neighbors as defined by the weighted neighborhood matrix (Anselin 1995, 1996). The LISA is closely related to the global Moran's I and gives evidence of the presence of spatial clusters and gives and intuitive tool for understanding the degree of spatial autocorrelation across variables and time (Anselin1995, 1998). The LISA statistic is a tool of a larger group of analytic tools used in Exploratory Spatial Data Analysis (ESDA), which is a collection of techniques used to describe and visualize spatial distributions; identify atypical locations and spatial outliers; discover patterns of spatial association, clusters, or hot spots; and suggest spatial regimes and other forms of spatial heterogeneity (Anselin 1992, 1994, 1998, 1999a). ESDA is an extension of Tukey's Exploratory Data Analysis (EDA), with special attention focused on the distinguishing characteristics of geographic data (Anselin 1989).

According to Anselin & Bera (1998) and Anselin (1988), the use of spatial methods allows for the controlling of potentially biased results and inaccurate inferences obtained from traditional methods which ignore these effects. These effects are caused by spatial dependence, which violates the basic assumptions inherent in classic linear regression. Two potential motivations for the use of spatial statistical techniques are to handle spatial dependence as a nuance and spatial dependence as a substantive issue (theory driven). As a result, two different spatial regression models are available for the analysis of data, spatial error models for the former and spatial lag models for the latter (Anselin 2000).

Geoda has a built in test called the Lagrange Multiplier test, which calls for the use of a spatial error versus a spatial lag model (Anselin & Kelejian 1997). Due to the increasing popularity and use of such methods there are now a number of packages that allow for many of the spatial procedures reviewed in this section (Anselin & Hudak 1992; Anselin & Smirnov 1998). However, the development of such technology is far from exhaustive and recently scholars have called for the continued usage of computer technology in the understanding global phenomena of all types. One such researcher, Hagerstand (2000), called for the implementation of computer based GIS in the development of more complicated and tedious research and pointed out that, to date, we are still not using the technology available to us, which could possibly help us to understand the effects of many of the processes we currently study.

Theoretical Framework

Overview

One of the reoccurring themes in this study is the importance of location in the determinacy and conceptualization of crime and covariates used to examine the phenomena. Currently in the field of demography, theories of location are becoming of greater importance because of the changing population dynamics associated with new technological advancements and the ever-developing global society (Anselin 1998; Goodchild and Janelle 2004). Such advancements make it possible to transcend historical geographic boundaries and spatial limits. In fact, these advancements in a sense devalue the once "priceless" commodity of geographical closeness, making it possible to maintain communication and carryout regular business operations without traditional concerns of proximity. Furthermore, these advancements seem to go in opposition to the classic statement concerning space: "location, location, location".

Along with these advancements, and the corresponding population shifts, have come a number of location-specific and spatial theories that have developed as a way to help explain and forecast current and future population trends and the social phenomena that undoubtedly are directly affected as a consequence. Many of these theories claim to be of great importance as both indicators of structural forces within society and as valuable sources of information for individual policy-makers and the government at all levels. The explanatory value of such information could ultimately lead to the more equal distribution of resources and, in the event of forecasts, could allow for the appropriate infrastructure development necessary to support future population and predicted shifts in population. The development of location theory, while extremely valuable in the study of human population, does not have its roots in demography or even in the social sciences for that matter.

The roots of spatial theory lie deeply planted in the field of economics within such ideas as the Thunen Model of land use and Christaller's Central Place Theory (Haggert 1967). In these models the ideas represent logical use of space or location as a way to maximize earning potential, whether through land use in agriculture or the development of urban areas in the analysis of a hierarchy of places (cities and towns). These ideas were later combined with and applied to population as Losch's 1937 article, *Population Cycles as a Cause of Business Cycles*, illustrates. Such ideas eventually blossomed into the demographic spatial theories seminally introduced in the preceding paragraph. More recent attention has focused on the modern ideas of suburbanization and the rural and urban fringe areas. Furthermore, postmodern theories of location and space have developed which completely turn the traditional theories of location and space their head. For example, according to postmodernists urban areas no longer disperse from a singular central core and the problems associated with urban areas cannot be examined using the traditional theories or visual aides that have become out-dated.

Along the way other important developments have occurred and contributed to the continued development of spatial theory, such as the use of Thunen Model by Park and Burgess in *The City* (1925). Within this work the concentric zonal model was introduced by the researchers from the Chicago school as a further development of research initially from the seminal work of Galpin (1915) in the *Anatomy of a Rural Community*. As a whole, these developments have furthered the range of spatial and spatial theory and have helped develop the theory into a theory of population and people, therefore transforming this traditionally economic theory into one of importance to social scientists, demographers, and economic theorists alike. Following is a brief overview of the historical development of theories of location and space.

Classical Economic Theories of Location

One of the earliest and most accepted forms of spatial location theory in economics is that of J.H. Von Thunen (1783-1850), who was a German farmer and amateur economist. The Von Thunen model is concerned with the spatial arrangement of various land covers to the central city. It is important to note that this model was developed before the rise of industrial production and the development of factories and as a result this model is based on a number of limiting assumptions. Of primary concern to Von Thunen was the ability of farmers to grow and maximize profits, therefore the model was applied to a single farm as a way of planning the planting of crops based on their harvesting costs. The model is economically grounded in hopes of balancing land costs with transportation costs and is simple in structure as there are four rings of agricultural activity surrounding the central city.

The closest ring is where intensive farming takes place in order to reduce transport costs to the city. The third ring consists of timber and firewood for fuel and building, its placement was also determined by the fact that timber was heavy and hard to transport. Extensive field crops, which include grains, occupy the fourth ring because they keep longer than dairy and are much lighter than fuel. Finally the last ring in the model is reserved for ranching/animal products, which can be raised far from the city because they are self-transporting. From this model and the accompanying assumptions you can see that these ideas are very primitive and taken as is they are of almost no use to modern spatial theory. Of great importance, however, is the fact that these ideas provided the initial foundation on which other ideas built.

In 1933, Christaller's Central Place Theory (CPT) was published using many of the same ideas introduced by Von Thunen over a century earlier (Haggert 1967). CPT, like the Von Thunen Model, was grounded in economics. However, unlike Von Thunen's model, CPT realized the city is neither isolated nor is it self-sufficient, and, based on that idea, Christaller developed a hierarchy of cities or towns. This hierarchy was developed based on two basic concepts; (1) threshold-the minimum market needed to bring a goods seller into existence and keep it in business and (2) range-the maximum distance people will travel to purchase goods. The range then was further spatial divided based on lower or higher order goods, lower order goods were those which consumers need frequently and therefore are less likely to go far distances for them and higher goods visa-versa.

Christaller’s theory is also concerned with a central trade center and the activity that disperses from that center. The threshold and the range are directly related to one another, primarily depending on the goods being sole. In larger central trade centers (large cities), which are more likely to have higher order goods the range would be much further than the threshold as people are willing to travel further for higher order goods. The smaller trade centers (smaller towns), the range is not very big as they are more likely to have only lower order goods and as mentioned earlier people are not willing to travel far for lower ordered goods. This then sets up a hierarchy of cities in which the larger cities with higher order goods are surrounded by a number of smaller towns as individuals can get lower ordered goods in their own small towns and were willing to travel to the larger cities for higher ordered goods. Current methods are still used today by a number of individuals including retailers who are looking into site analysis.

While Von Thunen and Christaller laid the basic groundwork for what would eventually develop into an important spatial theory in the social sciences, they were primarily concerned with economics and neglected to look at the role of populations or non-economic social relationships. One of the first to examine the role of location related to population was August Losch, whose 1937 article, *Population Cycles as a Cause of Business Cycles,* was published in an economics journal. However, he was one of the first to examine how economic changes were directly related to and perhaps caused by population changes. Thus, this reflected the introduction of location theory into a broader social sciences framework. Losch's approach was different from that of others concerned with the role of population in economics during the same time period as most took the Malthusian approach that population cycles were a *consequence* of the economy (Losch 1937). On the other hand Losch's thesis was the other way around stating that population is among the main *causes* of economic changes.

Losch was interested in the role societal advancements were having on the economy. Namely, the role of longer life expectancies and the increased burdens of the elderly, the increase in birth control and its effect on the capital market, and fluctuations in population increase (1937), the last of which he saw as effecting business through the large cycles of population movement. In his analysis, Losch introduced a number of relatively sophisticated co-variation tables examining population cycles and economic cycles. In his final analysis, he simply showed the significant role increases in population played in the further development of the economy and thereby tied together many of the traditional economic theories of place with the demographic ideas of population transitions and cycles.

The Chicago School

The use of location can be seen as a trademark of a number of professors associated with Chicago School sociology in that much of their work was focused in the city of Chicago and was based on spatial zones throughout the city which helped to characterize a person based on predicted attributes. *The City* (Burgess and McKenzie 1925) introduced an idea that would come to be known as the zonal hypothesis, following on earlier work put forth by rural sociologist Galpin's *Anatomy of a Rural Community* (1915). Burgess and McKenzie's hypothesis posited that the city of Chicago could be seen as a central core with rings dispersing outwards much like the Von Thunen economic model. The rings then would indicate particular zones that could be labeled based on their characteristics. The original hypothesis had five zones: (1) Central Business District, (2) Transition Zone, (3) Workingman Zone, (4) Residential Zone, and (5) Commuter Zone (Park 1925). Each zone can be seen as pushing outwards into the next zone from the Central Business District. Illustration 3 helps to show the Zonal Hypothesis and gives some defining characteristics of each zone.

One of the primary objectives of their original research was to help explain where and why crime occurred in the city. They believed the Transition Zone was the locality that would have the highest occurrence of delinquency, which seems to be obvious considering it consists of deteriorated housing, factories, abandoned buildings, and recent immigrant groups; all of which were seen as predictors of high crime areas in early urban sociology.

Recent Trends in Location Theory

As with a most theories and ideas throughout academia, spatial theory and other theories of space have come under attack by the recent rise attention given to the postmodern movement. One of the leading writers on the postmodern movement within theories of location is geographer Michael Dear.

Although Dear is a geographer, his primary interest is that of Social Geography or Human Geography and the relationship of space to social theory. Dear sees the postmodern movement as the perfect opportunity to reconstruct human geography in hopes of ultimately realigning it with social theory. He goes on to explain the effect of such a process as: (1) repositioning geography to have a central position within the social sciences, (2) recasting the internal structure of the discipline (geography), (3) reforging geography's links with the mainstream debates in the philosophy and method of the human sciences (Dear 1988).

In integrating human geography and social theory[3], Dear is concerned with the role of social theory as the "illumination of the concrete process of the everyday life" (Dear 1988). Human geography, then, can be constructed as a part of social theory that focuses on the "spatial patterns and processes that underlie the structures and appearances of everyday life" (Dear 1988). According to Dear this would help to compensate for a common problem in almost all social sciences, which is the ability to explain human behavior through the use of time and space. Society then is best understood as a time-space continuum that is inscribed with the details of political, social, and economic life (Dear 1988).

He goes on to note that the use of history in the social sciences as a use of time in examining behavior is much farther along than the use of geography as a way of explaining behavior based on space or location. He further goes on to make the claim that by fully understanding the potential to which the use of human geography can help develop social theory, geography itself will re-situate itself in center of a newly defined paradigm on human inquiry (Dear 1988). Such a claim seems a little outlandish but the point Dear wants to get out is that human geography and the use location as a tool in social theory can have promising results.

Dear goes on to explain that human landscapes are created by knowledgeable actors (agents) operating within a specific social context (structure). Furthermore the structure is transformed by the agents making any narrative on the human landscape an account of the reciprocal relationship between long-term structural arrangements and short-term practices of individual agents (Dear 1988). This last statement shows the degree to which human geography is linked to social theory. Further proof of such a relationship is that social relations are constituted through space, constrained by space (boundaries), and mediated through space (Dear 1988). The use of location in social theory is an exercise in reflexivity in which any single locale is a complex synthesis involving the ever-evolving social processes and their relation to the above mentioned location-specific limitations (Dear 1988).

In a 1998 article, Dear helped to redevelop many of the traditional location theories mentioned above which tend to revolve around a central city in the Von

Thunian tradition. Dear's argument takes aim at urbanism from a postmodern point of view. In doing so he compares the Chicago School's Concentric Zonal hypothesis with that of a newly developing postmodern view of the city of Los Angeles from the aptly named Los Angeles School. If one recalls the Chicago School View of the city was one of a central business district and concentric zonal rings which dispersed outward forming layers of rings. Each of these rings then constituted a different neighborhood that could be characterized by the type of housing, crime rates, social class, etc., which existed within the ring.

The Los Angels School model uses a postmodern method of deconstruction to show that the Chicago School model is outdated and of little use anymore. The Los Angeles School model is not perfectly situated in concentric zones; it is instead a random layout of fundamental urban characteristics that more aptly make up the postmodern urban center. The Chicago School assumptions of uniform land surface, universal access to single central city, free competition for space, and the notion of outward development can be dismissed from a postmodern point of view, as they simply do not represent reality now nor in the preceding modern era. The development of the Los Angeles model then can be seen as the evolution of spatial theory that can take place as a result of deconstructing theoretical assumptions and reexamining the sources of current knowledge.

Also important in the role of space and location theory in general is the effect of such an ecological environment on the individual in terms of behaviors and, both individual and community level, action. This dissertation makes use of Human Ecology as a guiding framework for explaining the implications of place on the individual, while trying to tie the two together in order to understand potential interplay between core places and periphery non-places (outlined and explained in greater detail below).

The following section provides a brief overview of human ecology with a specific emphasis on the interplay of the urban/rural classification based on such a framework. Furthermore, several leading theoretical approaches concerned with the spatial variations of reported crime will be introduced and outlined. These include two major strains of theory from the overarching ecological theoretical framework, social disorganization Theory and routine activities theory. The primary focus of the section, then, is to apply the role of Human Ecology to criminal offending and to the larger framework of spatial/location theory outlined in the above section.

Human Ecology and Inter-Place Relations

Perhaps the most influential and earliest account of human ecology was introduced by Amos Hawley in the aptly titled *Human Ecology* (1986). In

Hawley's work, he seems to setup the ecological foundation in which the maintenance and development of community takes place by positing certain assumptions and hypotheses involving both natural-environmental and demographic phenomena. In fact it is almost as if Hawley is aiming to develop an overarching theory that can come to explain all in the way of human's use of space and residential development.

According to Hawley communities develop and maintain themselves based on a series of defined parameters associated with two primary operationalizations (Hawley 1986). First, is the treatment of organisms, or individual actors, as completely autonomous and acting solely on some form of rational choice (Hawley 1986). The second definition of the organism is as a member of a collective with much less autonomy in a much more structurally coercive environment (Hawley 1986). In this type of an environment the actor relies to a lesser degree on rational choice and instead is conditioned through socialization, peer pressure, and various other social phenomena to embark on certain actions (Hawley 1986). As will be made clear in the *Ecological Theories of Crime Section*, the two should not stand alone in terms of theoretically predicting the occurrence of social actions. In fact, the two dominant theories within the ecological framework of criminology - one primarily structural and one primarily ration choice - are thought to be complimentary due to their comprehensive examination of both structural and agency factors in an integrated form (Smith et al. 2001).

Across all places in the U.S. there are a significant amount of both variations in both the rate of crime and the covariates that have been identified as predicators of crime rate levels, as is the case with most any social process (Land 1990, Land & Deane 1992, Land et al. 1991, Mandenka & Hill 1976, Wilson 1983, Boggs 1965, Schmid 1960a 1960b, Spector 1975, Danzinger 1976, Messner and Anselin 2004, Messner et al. 1999, Blau 1982, Crutchfield 2007, Ackerman 1998, Bloch 1949, Clinard 1944, Glaeser & Sacerdaote 1999, Paulson & Robinson 2004, Petee and Kowalski 1993, Wells & Weisheit 2004). Beyond these intra-place dynamics that lead to the existing ecology of an area[4], there are certain inter-place dynamics which may have just as much of an impact (Agnew 1993; Alber et al. 1971; Agnew 2002; Giddens 1984; Lightfoot and Martinez 1995; Gould 1964). Many researchers have identified such relationships between places and surrounding areas in a hierarchical fashion concerning the transmission of ideas and behaviors[5].

Ecological Theories of Crime

Developed in the 1920s, ecological criminology was one of the first sociological criminology theories (Paulsen and Robinson 2004). The "Chicago

School of Human Ecology", which later developed social disorganization theory, refers to a group of professors within the Department of Sociology at the University of Chicago and included a number of influential sociological theorists such as Mead, Park and Burgess, among others (Paulsen and Robinson 2004).

As mentioned above, ecology is referred to as the examination of relations between an organism and its environment and ecological theory explains crime by the disorganized areas where people live rather than by the kind of people who live there so it is easy to understand why social disorganization theory had its origins in the study of ecology. Prior to the development of social disorganization theory, there were a number of researchers, at the University of Chicago, exploring the effects of ecological factors of crime (Paulsen and Robinson 2004). However, it was not until much later, in the 1970's, that Oscar Newman, in *Defensible Space*, and C. Ray Jeffrey, in *Crime Prevention Through Environmental Design*, brought this perspective to the forefront in criminology (Paulsen and Robinson 2004).

Newman argues that residential areas such as high-rise apartments lack clear owners, are open to use by many and, therefore, residents cannot assert responsibility for their own safety, leaving such areas vulnerable to criminal activity. Newman developed the concept of "defensible space" to refer to "a residential environment designed to allow and even encourage residents themselves to supervise and be seen by outsiders as responsible for their neighborhoods" (Paulsen and Robinson 2004:81). The goal of these areas was to reduce opportunities for crime, encourage people to contribute to their own safety and enhance their sense of community and areas that lacked such characteristics were thought to be more vulnerable to crime (Paulsen and Robinson 2004). Newman's ideas were very influential throughout the 1970s and 80s and some of the crime prevention strategies put in place due to their research include controlling access (or reducing accessibility), increasing surveillance, activity support and reinforcement, or in other words, defensible space and target hardening (making it more difficult for an offender to gain access to a target or crime victim), changing traffic patterns, establishing community groups and strengthening police-community relations (Paulsen and Robinson 2004:84-85).

C. Ray Jeffery, similarly founded the term "crime prevention through environmental design" or "CPTED" (Paulsen and Robinson 2004). It, too, is based on the idea that crime results partly from the opportunities presented the physical environment and "is aimed at 'identifying conditions of the physical and social environment that provide opportunities for or precipitate criminal acts… and the alteration of those conditions so that no crimes occur…'" (Paulsen and Robinson 2004:86-7). However, in later works, Jeffery adds a biological element to his model. Jeffery argued that criminologists, up until that point, focused too heavily on the social factors on crime and not enough on biological and environmental factors. He introduced a new approach, the "integrated systems model" of human behavior, which purported that organisms and environments have a reciprocal relationship, continually influencing one another (Paulsen and Robinson 2004:88). Jeffery states,

> *"The response of the individual organism to the physical environment is a product of the brain; the brain in turn is a product of genetics and the environment. The environment never influences behavior directly, but only through the brain. Any model of crime prevention must include both the brain and the physical environment" (Paulsen and Robinson 2004:89).*

Therefore, crime prevention should focus on either/both the person committing the crime (the organism) or the place where the crime occurs (external environment) (Paulsen and Robinson 2004). He thought that crime prevention, then, should consider biological factors such as lead exposure, thought to cause brain damage and childhood delinquency, and reducing the environmental opportunities for crime in the immediate environment (Paulsen and Robinson 2004).

Both Newman and Jeffery were met with criticism from criminologists. Newman was accused of "environmental determinism" and many thought he oversimplified the problem by ignoring some important social factors such as poverty, unemployment and racism (Paulsen and Robinson 2004). Despite these criticisms, many "defensible space projects" were funded and implemented during the 1970s and 80s but evidence suggested that they had little impact on the incidence of crime in most cases (Paulsen and Robinson 2004). Jeffery's work was largely ignored by criminologists and in some cases was met with severe hostility, primarily in response to the biological argument. Like defensible space projects, the CPTED projects that were developed had little success but have led to the development of other related and more successful crime prevention measures. From these first attempts to explain crime in relation to ecology, a number of theories emerged.

Spatial/ecological approaches to the examination of crime tend to lend most of their attention to the interaction of crime and both the structural and individual covariates which lead to offending. Within this framework, most of the focus is on two primary theoretical orientations from which most of the other ecological theories tend to draw their roots (Smith et al. 2000). The two theories are social disorganization and routine activities theory. The first of these two is social disorganization Theory, which is concerned with the prediction of crime based on community characteristics concerned with socioeconomic status, racial/ethnic heterogeneity, residential stability, and urbanization (Smith et al. 2000; Bursik 1988; Bursik and Grasmik 1993; Farrington et al. 1993; Sampson and

Groves 1989). The second is routine activities theory, which is a rational choice agency based theory of criminal offending (Paulsen and Robinson 2000; Smith et al. 2000). This theory allows for both a comparative and complimentary examination of the ecology of crime, when examined alongside the social disorganization framework.

Social Disorganization

The roots of social disorganization theory originated with scholars at the University of Chicago, but it was not until 1958 that the concept of social disorganization was defined. "Thomas and Znaniecki defined social disorganization as a 'decrease of the influence of existing social rules of behavior upon individual members of the group'" (Paulsen and Robinson 2004: 54). Modern social disorganization theory, however, built on the ideas of Park & Burgess' concentric zone theory (1925) and, more famously, Shaw & McKay's cultural transmission theory (1942). More recently, Veysey and Messner (1999) gave an explanation of social disorganization within communities. They suggest "that social disorganization operates 'through the processes of value and norm conflicts, cultural change and cultural vacuums and the weakening of primary relationships. This, in turn, is believed to reduce internal and external social control, which then frees individuals to engage in deviant behavior'" (Paulsen and Robinson 2004:61). Therefore, according to Veysey and Messner, there are specific characteristics of the community that inhibit the ability to exhibit social control over its members, including racial heterogeneity, SES, single-parent households, etc. (Paulsen and Robinson 2004).

Social disorganization theory attributes variations in crime to a breakdown in the basic social institutions within a community such as family, school, church, etc and a breakdown of the relationships and networks between people within the community. As a result, social disorganization theorists believed that delinquent traditions emerged in some communities and were culturally transmitted from one generation to the next. When social disorganization is present in a community, there are fewer positive influences (i.e., community organizations, adult supervision) and more negative influences leading to a greater likelihood of associations with deviant peers from which to learn deviant behavior. These associations contribute to the perpetuation and spread of social disorganization (Paulsen and Robinson 2004). A community high in "collective efficacy" is thought to be the direct opposite of one high in social disorganization and, unlike the latter, the former knows how to maintain order is organized to fight crime not perpetuate it (Paulsen and Robinson 2004:61). Sampson et al. (1997) developed the term collective efficacy and suggested that in order to have it, a community must first have social capital, which they referred to as having many positive informal networks to rely on.

Community level factors suggested to contribute to social disorganization include structural characteristics such as high population density, high levels of transience, high poverty and physical decay (Paulsen and Robinson 2004). Stark's *theory of dangerous places* (1987) suggests that "factors in the physical environment lead to moral cynicism among residents, to increased opportunities and motivation for crime and interfere with the ability of residents to control the behavior of those who occupy the space" (Paulsen and Robinson 2004: 64). Other related factors include SES, residential instability, racial heterogeneity, etc.

> *"SES affects both organizational participation and supervision of peer groups. Poor communities lack money and resources, and therefore, have fewer organizational opportunities for youth and adults. In addition, poverty is believed to undermine formal and informal social controls, thus affecting the community's ability to monitor youth. Urbanization is negatively related to friendship networks and reduced organizational participation. Ethnic heterogeneity reduces community consensus and increases distrust among community members. Communities then become fragmented along ethnic lines, which impedes communication and, therefore, effective supervision of youths. Family disruption directly affects community members' ability to supervise teenage peer groups. Finally, residential mobility is predicted to disrupt friendship networks" (Paulsen and Robinson 2004:66).*

There are some important criticisms of social disorganization theory. One of the most significant of these is that social disorganization theory is limited in the *types* of crimes in can explain. It cannot explain individual level crime and is primarily aimed at explaining variations in crime rates (Paulsen and Robinson 2004). Another significant criticism of social disorganization theory is the lack of a direct measure of social disorganization. "According to Veysey and Messner (1999), 'Indicators for many of the structural elements thought to cause social disorganization, such as poverty and residential mobility, are routinely collected, but direct indicators of social disorganization are lacking in standard data sources" (Paulsen and Robinson 2004: 73).

Routine Activities Theory

The second theoretical approach that will be used in this examination is routine activities theory, which unlike social disorganization, is more concerned with rational choice as opposed to structural determinism (Smith et al. 2000; Cohen and Felson 1979; Beavon et al. 1994; Clarke 1994a, 1994b, 1996; Felson 1986, 1994). routine activities theory posits that crime occurs in specific locations based on the confluence of a number of important issues. First, there must be a suitable target, which may include individuals or property that is viewed as 'worth committing a criminal act against'. Next, there must be a motivated offender, which is often related to the relative depravation of criminal offenders in the form of poverty, unemployment, and other class related covariates. Lastly, there must be a lack of a capable guardian, which may be measured in a number of different ways, most often it is related to police strength and even to the ubiquity of ordinary citizens (Smith et al. 2000).

Routine activity theory, posed in 1979 by Lawrence Cohen and Marcus Felson, was conceived in an attempt to answer a seemingly paradoxical question within sociology: Why did urban crime (specifically predatory crimes involving direct physical contact between offender and victim such as rape, robbery, burglary, theft, etc.) increase during a period in which various social and economic conditions (education, family income, poverty, etc.) thought to contribute to the occurrence of crime improve? Cohen and Felson suggested that the answer to this question lies in the "structural changes in the routine activities of everyday life" (p. 589). The authors argue that such changes influence crime rates by affecting the convergence of specific persons or objects at specific locations in space and time (Cohen and Felson 1979). Whereas previous theories of crime focused primarily on the characteristics and motivations of the criminal, routine activity theory shifted the focus away from the criminal toward the criminal act itself and the surrounding circumstances.

According to Cohen and Felson, a successful completion of a criminal act minimally requires the convergence of three necessary components: (1) a motivated offender, (2) a suitable target and (3) the presence or absence of a capable guardian. A *motivated offender* is one that has both criminal intentions and the ability to carry out those intentions (Cohen and Felson 1979). A *suitable target* is identified by the offender based on "the perceived value, visibility, accessibility and inertia of the objective" (Boetig 2006: 2). In other words, while carrying out routine activities, a target is identified by an offender based on being the right person, in the right place, at the right time. After a motivated offender has identified a suitable target, "the presence or absence of a *capable guardian* becomes a determining factor in the actual commission or deterrence of a criminal event" (Boetig 2006: 2). For example, the presence of a neighbor or burglar system may be a deterrent against victimization (Boetig 2006). Moreover, Cohen and Felson point out that the lack of any one of these components can prevent a criminal act from occurring or at least from being fully carried out.

Over time, communities evolve as do the routine activities of those within that community (Cohen and Felson 1979). It is these changes or "social adjustments" that allow for the convergence of these components (Cohen and Felson 1979) and, consequently, allows for "illegal activities to feed upon the legal activities of everyday life" (p. 590). Routine activities, according to Cohen and Felson, affect the location and visibility of property and targets at particular times and, therefore the likelihood of a crime occurring. Even if there are no changes in the proportion of motivated offenders or suitable targets, "changes in routine activities can alter the likelihood of their convergence in space and time creating more opportunities for crime to occur" (Cohen and Felson 1979: 589). For example, a person in a group is less likely to be targeted than a person who is alone. Likewise, some activities may allow a person to have a weapon on hand for protection. On the other hand, an activity may distract or preoccupy a person making them less likely to discourage or resist an offender (Cohen and Felson 1979).

Routine activity theory, therefore, implies that crime is normal and depends primarily on the opportunities available. If a target is not protected enough, and if the reward is worth it, crime will happen. This has an undeniable influence of rational choice theory tied to a higher level of structural determinism in the fact that, while individual make an individual level choice to offend, individuals are directly tied to a given place within the larger ecology of the community, which in turn makes them more or less likely to be motivated offenders in search of opportunities for offending.

Hypotheses

From the previous literature review and methodology chapters it is now appropriate to formally state a set of testable hypotheses. These hypotheses draw on theoretical frameworks concerning criminological processes, contagion/mobility/diffusion, and location theory using recent developments in spatially centered analytic methods. This analysis specifies substantively meaningful place/non-place geography, which will further help to clarify current issues in the literature concerned with the correct unit of analysis for the examination of crime patterns and processes. Finally, these hypotheses will be tested via a set of appropriately specified models, laid out following the formal presentation below.

Up to this point the relevant hypotheses of this project were initially only implicit in nature and were not directly stated nor related to any of the relevant literature in a formal manner. Again, the proposed analysis will take place in three phases and each is laid out formally in the methodology section (Chapter III).

Hypotheses: Phase One - Description

1. The first phase and associated hypotheses is descriptive in nature. It sets the stage for the rest of the analysis. The analysis begins with the premise that patterns of criminal offending are non-random, and in particular will exhibit spatial autocorrelation.

a. It is hypothesized that in the U.S., for both 1990 and 2000, The Moran's I statistic for spatial autocorrelation of criminal offending will be positive for all three type-specific crime rates.

b. Likewise, it is hypothesized that significant differences will exist by place-level classification, which is to be examined using a repeated measures ANOVA with an expected significant F-statistic.

Hypotheses: Phase Two – Explanation/Prediction

2. The second phase and sets of hypotheses are concerned with the determinants of crime and the potential differences between urban and rural areas. This section introduces a new mid-level geography between the county and census tract. This new level significantly reduces the variation of social factors contained within a county, but aggregates homogeneous into substantively meaningful ecological area.

    a. In relation to the first theoretical framework of interest, social disorganization Theory, it is hypothesized that higher levels of urbanization, racial heterogeneity, family disruption, and low socioeconomic standing will all lead to higher levels of criminal offending.

b. In relation to the second theoretical framework of interest, routine activities theory, it is hypothesized that higher levels of motivated offenders, suitable targets, and lower levels of capable guardians will all lead to higher levels of criminal offending.

c. Lastly, it is hypothesized that, controlling for all other variables in the respective models, significant place-level effects will be identified.

Hypotheses: Phase Three – Spatio-Temporal Diffusion

3. Finally, phase 3 is concerned with the exploratory examination of the temporal spatial mobility and articulation of crime from 1990 – 2000, among and between urban and rural areas. Within the literature review there are competing theories pertaining to the contiguous articulation of social processes and behavior, as well as their associated vehicle of transmission (Park 1925; Agnew 1993; Lightfoot and Martinez 1995). Two of the spatial models related to the 'diffusion' of theses processes are the contiguous concentric zonal model and the non-contiguous hierarchical Los Angeles model. The latter concerns a much more spatially dispersed and random pattern, whereas the former is concerned with the, adopted, theoretical framework useful through the application of methods on the diffusion and

spread of innovation and applying them to a simple model of spatial mobility over two the temporal period of 1990 - 2000.

a. It is formally hypothesized that the significant relationships concerning the mobility of crime between places to NPT's from 1990 to 2000 can be identified as a process of spatial mobility in a contiguous manner, via the implementation of the multivariate LISA statistic. However, as is a theme with this study, it is hypothesized that those patterns themselves will be non-random and tend to occur in select regions of the country.

CHAPTER III

METHODOLOGY

Sources of Data

The data used in this study were obtained from a number of different sources, all ultimately pertaining to sub-county geographic areas within the contiguous 48 states. Data concerning reported crimes and policing strength were obtained from the agency-level UCR for both 1990 and 2000, while all other independent variables of interest were obtained from the summary files of the 1990 and 2000 respective decennial census. Geographic data were obtained for the years of 1990 and 2000 from the U.S. Census Bureau's Cartographic Boundary website (http://www.census.gov/geo/www/cob/). The data will be examined via number of spatially centered analytic techniques concerned with the predictive and stochastic modeling of total crime, violent crime, and property crime.

Uniform Crime Reporting Program

The primary source of data for the dependent variable of interest is the Federal Bureau of Investigation's Uniform Crime Reporting Program (UCR). The principle investigator for the Uniform Crime Reports is the United States Department of Justice. Within the Department of Justice the data collection effort is headed and compiled by the Federal Bureau of Investigation (F.B.I.). The reports are the only comprehensive count of crime data in U.S. and have recently become able to be merged with other data sources through a newly developed agency crosswalk described in greater detail later in this paper. The dataset is available at both the county and the agency level; both will be discussed below.

The Uniform Crime Report data series has been compiled since 1930 by the Federal Bureau of Investigation. The F.B.I. collects the data for the larger principle investigator, The United States Department of Justice. Across all years there are approximately 16,000 reporting agencies per year and for the year analyzed in this report (1990) there are 17,608. The approximate 16,000 reporting agencies from year to year across the life of the study accounts for about 90% of all law enforcement agencies in the U.S. County level data is aggregated from the appropriate agencies mentioned above. Currently data is available at the Inter-Consortium for Political & Social Research (ICPSR) housed at the University of Michigan from 1976-2000.

The data compiled in the agency-level UCR is made up of a four-part collection: 1) Offenses and Clearances by Arrest, 2) Property Stolen and Recovered, 3) Supplementary Homicide Data, 4) Police Employee Data. The primary dataset of the program is the Offenses and Clearances by Arrest; however the other datasets include important supplementary information. The Property Stolen and Recovered data covers, more in depth, the type of property stolen and recovered as well as important information regarding the crime. The Supplementary Homicide Data does the same for information regarding the murders in the main data file. Finally, the Police Employee Data in made up of data on the number of employees within each agency, number full-time and part-time, etc. All of these data files are meant to supplement the Offenses and Clearances by Arrests and provide important, in depth, information that cannot be obtained from the primary dataset.

The primary dataset, Offenses and Clearances by Arrests offers raw counts of all seven index crimes and break them down into sub-groups. The seven index crimes in the most recent datasets include murder, rape, robbery, assault, burglary, larceny, and motor vehicle theft. Arson was included as an eighth index crime in some earlier datasets. As mentioned above, each of the index crimes are made up of a number of sub-crimes. For example, murder is made up of homicide, manslaughter, etc. Each of these sub-crimes are reported and aggregated in the dataset as both the sub-crimes and the aggregated index crimes are in the data file.

The dataset is rather simplistic and doesn't have much besides the above mentioned crime reports. The other variables included in the dataset are the agency specific ID code, the government ID, total population served, year of study, core city indicator, census division, numeric state code, zip code, and Metropolitan Statistical Area associated with agency if applicable. As one can see most of the non-crime variables are ID codes and geographic indicators.

Recently a crosswalk has been developed to link UCR data to other data sources using Federal Information Processing Standards (FIPS) codes from the Census Bureau. These FIPS codes are linked in the crosswalk to the agency ID and allow for the matching of a number of different types of data. Perhaps the most exciting of these data prospects are the ability to link the UCR data to Census data and to geographically reference the data using Geographic Information System (GIS) software. This allows for the mapping of the most complete set of crime statistics for the first time from the direct source.

Data are submitted voluntarily by all agencies in the United States. These agencies are comprised of city, county and state law enforcement agencies for the agency level database. These are aggregated by the appropriate county in order to obtain the county level database. Some of the agencies report directly to the

FBI and others report through state collection agencies, which in turn report the information directly to the bureau. The response is very high by survey standards. The final dataset each year contains approximately 90% of all law enforcement agencies. Once the FBI receives the data it is thoroughly checked for completeness and arithmetical accuracy. When data issues arise the bureau directly contacts the agencies to correct or explain the data errors.

Construction of Sub-County Geography and Data

All original data, concerning both the dependent and independent variables of interest, has been decomposed from the county level into the place non-place level, using the following equation 1 as the bases for the relationship between the three geographic units;

Computation of Non-Place Territory Data

$$County = \Sigma\ (Places) + Non\ Place\ Territory \tag{1}$$

From that equation one can see that the identity of the county is made up of nothing more than the sum of all of the places of a count plus whatever is left over, the non-place. That being the case and since data can be obtained at both the county and place level, it is possible to compute the non-place territory as the difference between the counties and places. Again an illustration of the place/non-place geography can be seen in Figure 1, documenting the use of the geography in the Golden Triangle Region (GTR). In the figure you can see the delineation between the units of analysis for this project, in which there are three major counties of interest and nine census defined places. Each of the places and each of the non-places (balance of the county) would have all associated independent variables at that level of geography, pertinent to their respective populations.

The development of the geographic coverage for analysis was somewhat more complicated. First, using basic GIS operations from the geo-processing wizard in ArcGIS, the place level polygons had to be clipped from the county level polygons, leaving a county level map with a number of "holes" where places used to be, akin to a piece of Swiss cheese. This coverage of counties, sans place polygons, is the spatial boundary of the non-place territory. Next, the place level polygons had to be merged back to the NPT, in order to fill in the holes left by the original operation. This resulted in a consolidated spatial data coverage with places and non-place territories in the same polygon file for a given year (e.g., 1990, 2000).

Measurement and Operationalization

Dependent Variables

The dependent variables consist of counts and constructed rates of crime obtained from the F.B.I.'s Uniform Crime Reporting Program (UCR). Following the literature, this study makes use of three separate variables at two different time periods. First, is the total crime rate, which is the sum of the seven index crimes reported to the F.B.I. The seven index crimes consist of murder, rape, robbery, burglary, assault, motor vehicle theft, and larceny. The variable is computed by simply summing all cases for each geographic unit, dividing that figure by the total population within that geographic unit, and multiplying it by 100,000, in order to compute a rate consistent with the literature. It is important to note that some of the earlier literature used eight index crimes and included arson, but more recently the literature has moved to using seven following the UCR programs omission of arson as an index crime.

The other two dependent variables will be subsets of the total crime rate consisting of violent crime and property crime. The violent crime rates will be computed via the same technique as the total rate using only murder, rape, and assault. Likewise the property crime rate will consist of only burglary, robbery, larceny, and motor vehicle theft. All rates will be per 100,000 population and all three crime rates will be computed for both 1990 and 2000, ultimately resulting in six independent variables across two time periods.

Based on the literature, Empirical Bayes' rates will be utilized as a parallel computation of the DVs so as to reduce the effects of rate instability and to allow for a clearer view of existing patterns that may be associated with each of the crime rates over the geographic study area ; Anselin's (2006).

Data Processing for the Dependent Variable

This section will outline the processing procedures for the dependent variables as well as UCR reporting program itself. The first step was to merge the year-specific UCR agency-level data with the appropriate UCR/Census ID crosswalk. In order to decipher between the two geographies (places and non-places) I used the 'INDEX' function in SPSS, which allows you to search a particular data field for important text strings. I searched the 'CNAME' field for the text "(County)". These 3,183 cases in 1990 and 5,936 cases in 2000 (agencies) that served the greater county (outside of places). These cases were then selected out and placed into a new dataset in which a FIPS field was created using only the string versions of the state and county FIPS code as an indicator of "out-in-the-county" ("non-place") crime incidents, creating a new five digit Non-Place FIPS code. The I.D. structure is illustrated in Figure 4.

Place_Level_ID	County_ID	AREA_NAME
1001	1001	Autauga, AL
100162328	1001	AL, Prattville city
1003	1003	Baldwin, AL
100304660	1003	AL, Bay Minette city
100319648	1003	AL, Daphne city
100325240	1003	AL, Fairhope city
100326992	1003	AL, Foley city
100332272	1003	AL, Gulf Shores city
100357144	1003	AL, Orange Beach town
100365208	1003	AL, Robertsdale city
1005	1005	Barbour, AL
100515376	1005	AL, Clayton town
100524568	1005	AL, Eufaula city
1007	1007	Bibb, AL
1009	1009	Blount, AL
100907456	1009	AL, Blountsville town
100957000	1009	AL, Oneonta city
1011	1011	Bullock, AL
101177880	1011	AL, Union Springs city
1013	1013	Butler, AL
101331912	1013	AL, Greenville city
1015	1015	Calhoun, AL
101501852	1015	AL, Anniston city
101538272	1015	AL, Jacksonville city
101557576	1015	AL, Oxford city
101559640	1015	AL, Piedmont city
101580352	1015	AL, Weaver city

Figure 4. Screenshot of Figure layout of ID Structure for Place/ Non-Place Geography

Next the place level agencies were processed. These agencies were reflected by all agencies left over from the above steps. They represented a total of 14,676 agencies in 1990 and 13,659 agencies in 2000. However, since we are concerned with ultimately matching these place level agencies to their appropriate place geographies using GIS, I dropped a number of agencies that did not have the appropriate characteristics. To do this we selected all agencies with the government type of county, municipal or township, in order to leave only agencies that directly served a census defined place. The county government type was used because there were a handful of county agencies that were not selected in the first go around and may in fact serve consolidated cities (Nashville, TN; Louisville, KY; etc.). The appropriate FIPS was computed for these cases as well by simply combining the string version of the State FIPS and the Place FIPS, creating a new seven digit Place FIPS code.

Next, I was interested in identifying those counties that were self-covered according to the 1990 UCR and those that were not. The 3,062 self-covered "non-place" agencies in 1990 accounted for >99% of all "non-place" crimes. Also, there were 9,859 places in 1990 that were self-covered which accounted for >99% of all place crime. The final results for the 1990 agency filed shows 2,972 total "non-places" (counties) covered by 3,183 agencies and 11,216 places covered by 11,306 agencies. The final file then contains 15,502,510 reported crimes (>97% of all

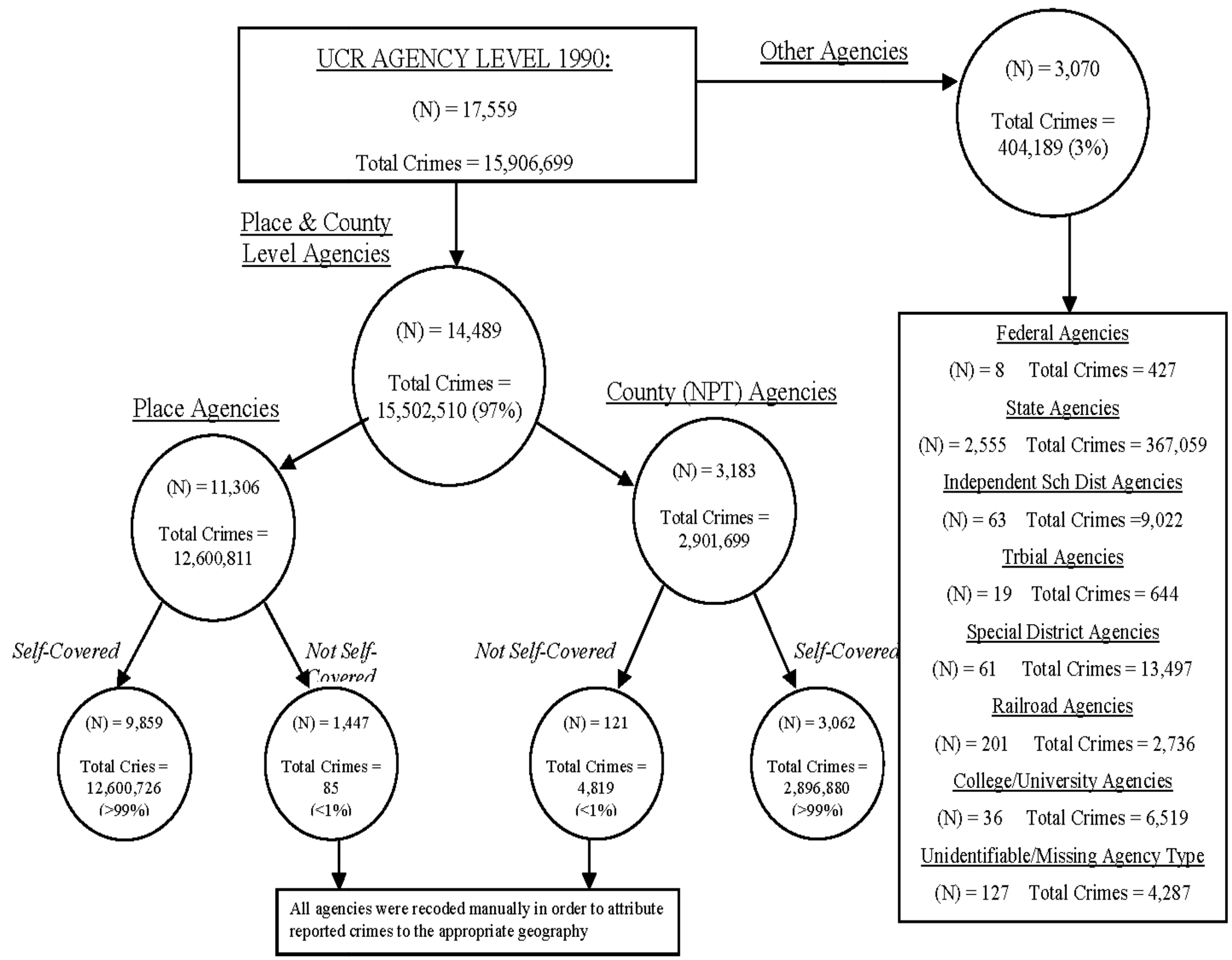


Figure 5. Data Processing of Dependent Variables, 1990

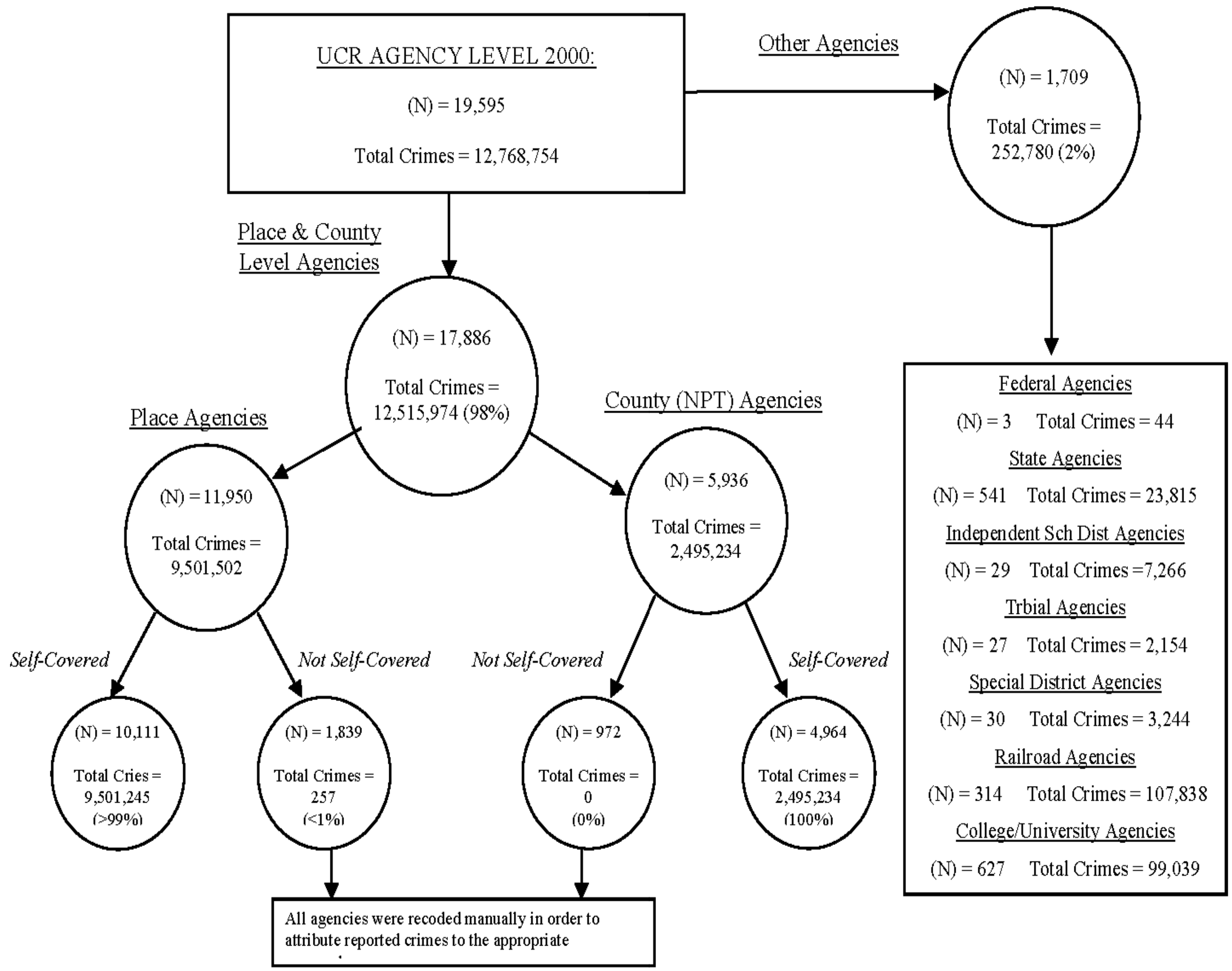


Figure 6. Data Processing of Dependent Variables, 2000

reported crime in the 1990 UCR) by 14,489 agencies. The results of the 1990 UCR data processing are graphically illustrated in flow chart form in Figure 5.

Similarly, in 2000 the 4,964 self-covered non-place agencies accounted for 100% of all crime and the 11,950 self-covered place level agencies accounted for >99% of all crime. All places and non-places were, then, aggregated by summing the total number of crimes for each place and "non-place" code. The final results for the 2000 agency file show 2,993 total "non-places" (counties) covered by 5,936 agencies and 11,879 places covered by 11,950 agencies. The final file, then, contains 12,768,754 reported crimes (>98% of all reported crime in the 2000 UCR) by 17,886 agencies. The results of the 2000 UCR data processing are graphically illustrated in flow chart form in Figure 6.

As illustrated, the structure of the dataset with the five digit codes representing the non-place territory of each county while the ten digit codes that follow represent all of the census defined places within the county of interest. The linkage to the greater county is evident as each of the place ID codes has the same first five digits as the non-place territory, which it follows. The final 1990 file contains 17,172 cases consisting of both Census designated places and non-place territory, while the 2000 file contains 17,063 cases of the same types. The consolidated merged 1990-2000 file contains 15,303 cases that were in existence and had data in both time periods.

Independent Variables

The independent variables in the study were obtained from a number of sources, again all pertaining to the contiguous forty-eight state region of the U.S. The U.S. Census Bureau's Summary Files (3,4) from the 1990 and 2000 decennial census provided data on the percent black, the median household income, residential segregation, the percent below poverty, percent of all households that were single female-headed, the total population size, population density, median age, the unemployment rate, the percent divorced, metropolitan status of the larger county, U.S. Census region, the percent housing pre-1940, median home value, percent of the population under the age of eighteen, the average rent, and the percent of housing units that were owner occupied. Per the literature review, all independent variables will be examined in order to make sure all analytic assumptions are met, including the absence of multicolinearity and the presence of normality. Where appropriate, data reduction techniques, such as principal components factor analysis, will be implemented to account for possible colinearity.

Data on the size of the police force were obtained from the UCR Law Enforcement Officers Killed and Assaulted (LEOKA) dataset. Each of the variables were selected based on their use in previous research and the tie they have to a theoretical grounding in the examination of crime. Table 1 outlines

Table 1. Variables of Interest for Place-Level Geographic Examination of Reported Criminal Offending

Dependent Variables		
Total Crime Rate		
Violent Crime Rate		
Property Crime Rate		

	Relation to Ecological Theoretical Framework	
Independent Variables	Social Disorganization	Routine Activities
* Percent Black	X	X
* Median Family Income	X	X
* Residential Segregation	X	
* Percent Below Poverty	X	X
* Percent Female Headed Households	X	X
* Population Size	X	
* Population Density	X	
* Unemployment Rate	X	X
* Percent Divorced	X	
Percent College Degree (BA)	X	X
Percent of Housing Owner-Occupied	X	
* Median Age		X
Percent Housing Pre-1940		X
Median Home Value		X
Percent of Popualtion Under the Age of 18		X
Percent of Popualtion Between the Ages of 18-24		X
Average Rent		X
Police Strength		X

Controls
* Metropolitan Status
* U.S. Census Region

* Included as a Covariate in Land et al. 1990

each of the variables and to what theoretical background they belong. As outline below in the model specification section the two primary theoretical frameworks implemented include are social disorganization and routine activities theory.

These are arguably the two most popular theories tying ecology and crime together (Smith, Frazee, and Davison 2000). Again specified in greater detail below, social disorganization is primarily concerned with the structural and macro-level effects of a "disorganized community" Smith et al 2000; Bursik 1988; Bursik and Grasmik 1993; Farrington et al. 1993; Sampson and Groves 1989). While routine activities theory is concerned with the agency related rational choice of an offender based on the intersection of specific components related to criminal activity (Smith et al. 2000; Cohen and Felson 1979; Beavon et al. 1994; Clarke 1994a, 1994b, 1996; Felson 1986, 1994).

As one can see, these two approaches have much in common, especially in terms of their sub-components which break down the larger theory into smaller groupings. This makes testing the theories much more convenient and allows for the independent and isolated examination the effects of each. However, the two theories are also quite different in that the social disorganization Theory focuses its attention on the structure using a determinist approach, while the routine activities theory takes more of an agency approach concerned with the ability to decide when all three components make the opportunity for crime to good to resist. These similarities and differences should allow for both an ease and exhaustiveness to the specification of the appropriate models concerned with the prediction of total, violent, and property crime for both the years of 1990 and 2000, as well as predictive models associated with the change in crime over the specified study period.

Data Processing for the Independent Variables

As with the dependent variables outlined above, the uniqueness of the units of analysis do not allow for the variables to be directly used as obtained from the data sources. The processing strategy for each of the independent variables will consist of a similar approach to that taken on the computation of the dependent variable. In this case data will be compiled for the census block-group level in order to aggregate raw numbers up to the county level. This can further be decomposed into the place and non-place level by using the decomposition equation mentioned earlier and matching each of the blocks to a specified place or non-place (NPT).

The use of G.I.S. in the processing of the Independent variables involves the use of a block-group coverage and the newly created place/non-place coverage outlined in the "Construction of Sub-County Geography and Data" section at the beginning of this section (Ormsby et al. 2001). Giving only a seminal review of the process, the two coverages are overlaid in geographic space so that each of the block-groups are nested within a larger place or NPT geographic area. Next, using the 'Union' function each of the bock-groups are matched to their encompassing place/NPT and a many-to-one database file is created which matches every block-group unit to the appropriate place/NPT. From here the same decomposition equation employed above with the processing of the dependent variable can be implemented.

For example, using the identity equation (County = Σ (Places) + Non-Place Territory) and the FIPS county code (first five digits of block-group identification code), all data will be collected in raw numbers of individuals and aggregated via a summation function to the place and county level. From there, the summed place-level data can be subtracted from the county total, leaving the raw number of individuals at the non-place level for each of the specified independent variables outlined above. Since the data is in a raw numbers format it can easily be computed into the appropriate format at it's new level of geography, i.e. percent. This procedure will allow for the development of a dataset, which includes both the dependent and independent variables of interest for each census place and for each region not in a census place (one per county). Again,

Figure 6 contains the case organization as mentioned above in the dependent variable section.

Analytic Techniques

The analytic strategy for this project is a panel design consisting of two cross-sectional points in time at the beginning and end of the ten-year period from 1990-2000. The analytical procedures implemented in this study are multiphasic and will be descriptive, exploratory and explanatory and be broken down into three separate chapters.

The first chapter will entail the spatial and statistical analysis of the variables of interest in descriptive form so as to understand the spatial patterns of reported across sub-county units in the continental U.S. In order to help get a better understanding of the spatial and statistical description, this first chapter will also examine simple differences in crime by place-type, region, and metropolitan status, and point in time. This chapter will allow for an initial understanding of the distribution of the three crime rates (total, violent, and property), both statistically and geographically.

The second chapter will be concerned with the explanatory predictive modeling of temporally static crime rates from 1990 and 2000 separately and the prediction of change in the crime rate from 1990 to 2000. These models are expected to be spatially centered in nature, depending on the results of Chapter 1, and will employ tests to examine the existence of violations of regression using the Ordinary Least Squares (OLS)approach. Based on those findings the appropriate types of models will be employed in a specific manner to be laid out later in this chapter.

Lastly, the third chapter will be an exploratory approach to the detection of possible spatial mobility of crime via a combination of a number of theoretical approaches outlined above. These frameworks include the core-periphery relationship associated with the transmission of information and behavior, the concentric model of spatial arrangement introduced by the Chicago School, and the contiguous nature of the transmission of information and behavior, based on the spatial arrangement of places within non-places, as a combination of the two.

The statistical procedure employed, in this third "exploratory chapter" will implement the bivariate LISA statistic as an extension of the work done by Cohen and Tita (1999). This is labeled as an exploratory approach due to the fact that, first the approach is part of a family of test know as exploratory spatial data analysis (ESDA) and, second because previous work has only implemented the use of the univariate LISA. However, it is anticipated that the use of the bivariate LISA, which is inherently designed to handle temporal analyses, can further add to the methodological value of this project.

Descriptive Analysis

The descriptive analysis contains multiple phases, with the first phase consisting of the simple statistical examination of all variables of interest in order to understand their distribution and their comparative differences across place-level, while further analyzing the data by region and metropolitan status where appropriate. Initially, all variables will be examined as a way of determining their normality and appropriateness for inclusion in a predictive analysis involving regression. Pending the results, all non-normal variables will be transformed until they are deemed to be appropriate for such analytic techniques.

Next, the second exploratory phase of the analysis involves the use of G.I.S. to map both the incidence rates and the smoothed rates, in order to visually identify the potential patterns associated with the type-specific crime rate. This portion will allow for the initial spatial examination of the dependent variables and is expected to give evidence of spatial non-randomness, meaning that further tests of spatial dependence are necessary in order to apply tests of significance to existing spatial patterns. A test for spatial dependence via the implementation of Anselin's LISA statistic will be used in order to test for possible spatial autocorrelation, or significant spatial non-randomness.

Lastly, the final portion of this chapter will be interested in the examination of mean differences across different categorical, and spatially centered, classifications. First, using a repeated measures method, all three type-specific crime rates will be examined in relation to one another. This test will examine differences in rates of crime between the Census defined regions, metropolitan status, place-level, and point in time. Furthermore, this analysis will examine all possible interactions within single model in order to test for the relative strength of each as a between unit classifier (Tabachnik and Fidel 2000).

It is important to note that, due to the large population size in this study most of my findings will be statistically significant (Ott and Longnecker 2000; Tabachnik and Fidel 2006). Based on that point, substantive significance will examined in extreme detail and post-hoc tests of magnitude will be implemented where appropriate. One such test implements the partial eta-square test as a post-hoc measure of variation in mean differences test (Ott and Longnecker 2000). This statistic acts the same as the r-square in regression, in that it returns a statistic that measures the variation in the dependent variable by the independent variable (Ott and Longnecker 2000). In the case of mean differences, it will attest to the magnitude of the variation in the type-specific crime rate that is accounted for by the limited categorical variables across which it's means are tested.

Explanatory Analysis

Based on the findings from the ESDA in the descriptive analysis, the explanatory analysis (2nd phase) will consist of a number of regression-based models using the appropriate techniques to control for the existence or absence of spatial autocorrelation. This approach is important due to the fact that this project deals with geographic data and the related idea that places closer together are likely to be more alike than those far apart. If that is determined to be the case, in this instance, it would indicate a violation of the regression assumption associated with independence concerning the random errors (Anselin 1995). In the event of obvious spatial autocorrelation from the descriptively centered ESDA, as expected via the literature review, spatial dependence diagnostics will be examined in Geoda in order to identify existing non-randomness associated with the random errors.

The spatial dependence diagnostics test used in this analysis will be concerned with a particular type of spatial effect, spatial dependence. The two causes of spatial dependence are error and substance (Anselin 1995; Messner et al. 1999; Brasier 2002). When spatial dependence determined to be error based it means that the autocorrelation among the variables is among the regression residuals and suggests that in fact there may be other explanatory variables, which have not been included in the model (Brasier 2002). In this case the spatial weight is applied to the error term in the regression equation. However, when the spatial dependence is determined to be related to substance, it suggests that the autocorrelation exists in the dependent variable itself (Brasier 2002). Unlike the error case, this time the spatial weight is applied to the dependent variable. From these results, the Langrange Multiplier test will be implemented in order to select the appropriate spatially weighted model.

Based on the determination of the type of spatial autocorrelation that exists, the second part of this chapter is concerned with the predictive modeling of crime rates in both static and change form. The dependent variables of interest will vary, based on the literature, and will consist of three types; total crime rate, violent crime rate, and property crime rate. Each of the three dependent variables will then be examined in a static form for both 1990 and 2000 and then in dynamic form in order to capture changes in rates of total crime, violent crime, and property crime from 1990 to 2000.

Exploratory Analysis of Spatial Diffusion

The final phase of the analysis consists of an exploratory analysis implementing a modified replication of Cohen and Tita's (1999) use of Anselin's univariate LISA statistic at two different time periods in order to identify possible processes of spatial diffusion. Within that study Cohen and Tita (1999) used the crime rate at two different time periods and created a rubric that they felt was able to interpret changes from one type of spatial clustering pattern to another over the time period. This implementation of the LISA statistic over time was very important to furthering the understanding of the interaction between crime in space and time.

However, the univariate method does not easily work as well as other options when modeling temporal diffusion or change. This is due to the fact that it has trouble accounting for the adopting location, which may, or may not, have been high on crime rate at time one (T1). The bivariate LISA, however, allows for the plotting of the crime rate at T1 against a second differing variable, giving a direct relationship between a specific cases crime rate at T1 and a measure of spatial relationship to other variables in the surrounding counties. This project will implement a bivariate LISA approach in order to examine the relationship between each county's crime rate in 1990 and 2000.

As mentioned above, the LISA statistic is sensitive to the definition of the neighborhood (Anselin 1995). Furthermore, it is important to define your given neighborhood as being grounded in some theoretical framework (Waller and Gotway 2004). In this case the neighborhood is to be defined using a number of differing approaches in order to maximize the within county relationships (Anselin 1995). Maximizing the within county connectivity is important due to the fact that one of the goals of this dissertation is to identify patterns of urban to rural crime diffusion within the same county. Implementing some of the work outlined above, the transmission of social processes, behaviors, and information is often found to take place in a core to periphery fashion (Agnew 1993; Lightfoot and Martinez 1995). It is evident then that the transmission of criminal behavior should move outward in a contiguous manner to the periphery areas, or non-places, from the core areas, or places. This method then should allow for the better understanding of the mobility processes of crime from the source outward in a contagious model of urban to rural criminological processes (Park et al 1920; Lightfoot and Martinez 1995; Agnew 1993).

Ultimately, this function will allow for both the intra-county examination of the spatial mobility of type-specific crime rate across the entire country and then, the proper specification of the spatial neighborhood, it will allow for the inter-county spatial mobility by not allowing geographic entities within different counties to be considered neighbors. Each of these are further outlined in the model specification section outlined in greater detail below.

Model Specifications

Descriptive/ESDA Model Specifications

The initial stage of the descriptive analysis will involve the simple statistical description of all dependent and independent variables used in this study. This will include univariate measures of distribution and bivariate correlations. The former will allow for the examination of each variable in order to verify that it is appropriate for further analyses, specifically that the variable is normally distributed. Non-normal variables will be transformed to regain symmetry so that it may be appropriate for subsequent analyses (Tabachnik and Fidel 2006; Ott and Longnecker 2000). The statistics used to make such a decision will be the skewness, kurtosis and normality plots. The results will be summarized in a descriptives table.

Next, bivariate correlations will be obtained for all continuous independent variables in the study in order to test for potential issues with multicolinearity. Similar test implementing a principal components factor analysis will be used to further test for multicolinearity problems (Tabachnik and Fidel 2006). Again, as in the initial stage concerned with statistical description, this process will ensure that the following regression analyses yield reliable and unbiased results (Ott and Longnecker 2000). This step in the analysis should yield a clean set of independent variables for future analyses.

Once a statistical description of all variables is completed, a spatial-oriented description will be undertaken via the mapping of raw rates, smoothed rates, and Exploratory Spatial Data Analysis techniques (Tukey 1977; Anselin 1995) . First, the raw rate will be mapped as simply the number of incidents of the type-specific crime rate (violent, property, and total) divided by the population at risk and multiplied by 100,000 as follows in equation 2:

Computation of Raw Crime Rate

$$E(Yi) = \frac{ri}{ni} * 100,000 \tag{2}$$

Within this equation *E(Yi)* is the expected rate based on the number of occurrences *(ri)* divided by the number of people in the geographic entity *(ni)*multiplied by 100,000 in order to standardize the rate per 100,000 individuals of the population. Multiplying the rate by 100,000 is important as it allows for the comparison of rates that would otherwise lack significant variation due to small numbers and a Poisson like distribution (Gotway and Waller 2004; Cressie 1993;).

This initial step in the spatial description of the data will give a seminal look at the distribution of sub-county crime across geographic space. For example, the earlier review of literature states that crime rates are higher in the South and West regions as well as in metro areas, in comparison to nonmetropolitan areas (Mandenka & Hill 1976, Wilson 1983, Boggs 1965, Schmid

1960a 1960b, Spector 1975, Danzinger 1976, Messner and Anselin 2004, Messner et al. 1999, Blau 1982, Crutchfield 2007, Ackerman 1998). However, these analyses were done at the county level and many times at a national scale. Work at a sub-county level has not been visually displayed at such a large scale. This dissertation examines a sub-county geography and visually displays it at a national scale, the aim will be to identify similar and differing patterns from the before mentioned literature concerning county level analyses.

From these maps the initial evidence of spatial randomness, or non-randomness) should be apparent; however it is important to note that raw rates are often not reliable visually as they are sometimes based on small numbers and high variations across neighboring places (Waller and Gotway 2004; Cressie 1993).

In order to account for this issue, a second set of maps will used to visually inspect the distribution of the rates of crime using smoothed type-specific crime rates. Smoothed rates take a "regression to the mean approach" by "shrinking" a single area's crime rate to the mean rate of all entities within a given area (Waller and Gotway 2004). In this case the neighborhood is equal to all "touching" geographies (i.e., a queen's definition; see Anselin 1988; Cliff and Ord 1981; Bailey and Gatrell 1995). The Local Empirical Bayes Smoothing (LEBS) (Gotway and Waller 2004; Clayton and Kaldor 1987; Carlin and Louis 2000;

Gelman et al. 2004; Marshall 1991; Bailey and Gatrell 1995; Besag et al. 1991) will be employed in order to create more reliable patterns in the geographic distribution of the data. The LEBS rate is computed by this formula:

Computation of Local Empirical Bayes Smoothed Crime Rate

$$\Lambda i = \mu i + ci(ri - \mu i) \qquad (3)$$

where the LEBS (λi) is a weighted average computed by adding the expected mean rate of the neighborhood (μi) to the shrinkage factor (*ci)*, which is multiplied by the raw rate (*ri)* minus the mean of the neighborhood (μi). Since *ci* is the rate of overall variance to the raw rate variance, when *ci* is small the Bayes estimator is close to the overall mean μi, likewise when it is large the estimator is approaches the raw rate (*ri*). The estimators are called 'local' because of the subtraction of the neighborhood mean from the raw rate, as opposed to the global mean from the raw rate. The former causes the "regression" towards the mean to take place on a neighborhood level allowing for maximum variation among smoothing techniques (Waller and Gotway 2004; Clayton and Kaldor 1987; Carlin and Louis 2000; Gelman et al. 2004; Marshall 1991).

The advantages of using a smoothed rate include the ability to stabilize raw rates and the reduction of 'noise' caused by raw rates computed from different population sizes (Waller and Gotway 2004). Along with the advantages, the smoothed rate also has some disadvantages that must be mentioned. First, smoothed rates are not the actual rates that will be used in further analyses. Instead the focus is on a geographic intensification of stabilized rates, which itself helps to identify spatial patterns in the data (Waller and Gotway 2004; Clayton and Kaldor 1987; Carlin and Louis 2000; Gelman et al. 2004; Marshall 1991). Also of import is the fact that the use of smoothed rates may simply substitute unstable estimates for correlated estimates, meaning that, in a sense, one is still looking at unreliable rates (Waller and Gotway 2004). Despite these noted disadvantages, smoothed rates are important to this study as visual aids in the detection of reported criminological offending across space.

Up to this point in the analysis, all inspections of spatial patterns have been partly subjective, primarily relying on the visual interpretation potential patterns. In order to apply a test of significance to such patterns, indexes of spatial autocorrelation will be employed. For this phase of the analysis both a global and local measure of spatial autocorrelation will be used, the former testing for an overall clustering pattern and the latter testing for local pockets of similar areas which significantly deviate from the mean (Waller and Gotway 2004). If, in fact, spatial dependence is identified then it lends the final piece of evidence needed to implement a battery of spatially weighted autoregressive predictive models in the second phase of this analysis. If it is not detected, then regular OLS regression is deemed to be appropriate based on the assumption the random errors are uncorrelated (Anselin 1995; Waller and Gotway 2004).

The most important single statistic associated with this portion of the analysis is the Moran's I index. Within spatial statistics, this index is widely used as a direct indicator of similarity and distance (Waller and Gotway 2004; Griffith 1992; Cliff and Ord 1973, 1981; Mantel 1967; Haining 1990; Bailey and Gatrell 1995; Fingelton 1985; Besag and Newell 1991; Walter 1992a, 1992b; Tiefelsdorf 2000; Oden 1995). In general Moran's I is computed by the following formula:

Computation of Global Moran's I Coefficient

$$I = \left(\frac{1}{s2}\right)\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_{ij}(Yi-\overline{Y})(Yj-\overline{Y})}{\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_{ij}} \tag{4}$$

Where:

$$s2 = \frac{1}{N}\sum_{i=1}^{N}(Yi-\overline{Y})\wedge 2$$

In the above equation the measure of spatial dependence is equal to a measure of variation in the area unit specific rate and the overall mean rate (s^2) is multiplied by the neighbor weight indicator (ω_{ij}) times the product of each unit (i) minus the overall mean and each neighborhood (j) minus the overall mean then divided again by the weight indicator and summed across all units (i)and across all neighborhoods (j) (Waller and Gotway 2004; Griffith 1992; Haining

1990; Bailey and Gatrell 1995; Fingelton 1985; Besag and Newell 1991; Tiefelsdorf 2000). The statistic is very similar to Pearson's Correlation Coefficient in that it measures an association between *N* observed values associated with two random variables, *Xi* and *Yi* (Waller and Gotway 2004). In this case the only difference is replacing the *Xi* variable with the *Yj* neighborhood variable.

This equation produces is a statistic in which each unit's (i) interaction with another is taken to account and when neighboring units (indicated by a 1 as the ω_{ij}, as opposed to a zero for non-neighboring units) are similar the Moran's I statistic is positive, meaning closer areas tend to be more alike than those far apart (Waller and Gotway 2004; Griffith 1992; Cliff and Ord 1973, 1981; Mantel 1967; Haining 1990; Bailey and Gatrell 1995; Fingelton 1985; Besag and Newell 1991; Walter 1992a, 1992b; Tiefelsdorf 2000; Oden 1995). In this instance you would have spatial clustering. In order to place a significance value on the observed Moran's I statistic, a permutations based tested will be implemented to test the null hypothesis: "No spatial autocorrelation". The test uses a set number of permutations to test the global index on randomly assigned locations in order to approximate the distribution of the global index under the null assumption (Waller and Gotway 2004). This project will implement a 999 permutations test with a reject region equal to a 0.05 significance level.

If the Moran's I statistic is deemed to be statistically significant the predictive phase two portion of the analysis will implement tests to choose the correct autoregressive model. Again, as mentioned earlier, the Lagrange multiplier test will be implemented on each OLS model to identify spatial error or spatial lag as being evident among the geographic data (Waller and Gotway 2004, Anselin 1995, 1988). Again, in the presence of spatial dependence as indicated by a significant Moran's I coefficient, the correct specification of autoregressive models will control for correlated random error terms among the geographic units of analysis, thus resulting in unbiased parameter estimates (Anselin 1995, 1988).

Once the statistical and spatial description have been implemented and the tests for spatial dependence have been run and tested, the last portion of the descriptive phase will examine the differences in means across three geographically defined and one temporally defined set of categorical variables. First, a multiple comparisons approach will test the difference in means across all four census regions and all three metropolitan proximity categories identified above. Also, a one-way ANOVA will be implemented to test the difference in means between places and non-places and lastly places and non-places will be compared to themselves across the two cross-sections of time, 1990 and 2000. While all comparisons will help to better understand the geographic and temporal nature related to the distribution of criminological offending, the comparison between place and non-place, is most significantly related to the substantive interest of this project.

In all cases, box-plots will be presented in order to visually display the potential differences in means across all groups. Next, the variation within each category will be compared to the variations between each category in hopes of identifying significantly different expected type-specific crime rates based on the above mentioned categorizations, via the F-statistic in the ANOVA table. In the case of the multiple comparison cases, all categories will be tested pairwise against all other categories via Fisher's Least Significant Difference (LSD) test.

The culmination of the difference in means test will wrap the descriptive portion of the analysis for this project. From the results, much will be known about the statistical and spatial distribution of type-specific crime rates for both 1990 and 2000. Also, differences among differing categories associated with the variables will be tested in order to identify significant variation between groups and lastly, tests for spatial dependence will be implemented in order to test for the significant role of space associated with the dependent variables. Again, the identification of spatial dependence will ultimately decide the type of predictive analyses implemented in this project.

Explanatory Regression Model Specifications

The second phase of the analysis is interested in the predictive modeling of type-specific crime rates based on the above literature review and two primary ecological theories of crime. Most of the spatial/ecological approaches to the examination of crime focus on two primary theoretical frameworks from which others tend to draw their roots (Smith, Frazee, and Davison 2000). The first of these two is social disorganization Theory, which is concerned with the prediction of crime based on community and individual characteristics concerned with socioeconomic status, racial/ethnic heterogeneity, residential stability, and urbanization (Smith et al. 2000; Bursik 1988; Bursik and Grasmik 1993; Farrington et al. 1993; Sampson and Groves 1989). The intersection of undesirable characteristics associated with each of the four components leads to a socially disorganized community, which is theoretically more susceptible to crime.

The second theoretical approach that will be used in this examination is routine activities theory, which unlike social disorganization, is more concerned with rational choice as opposed to structural determinism (Smith et al. 2000; Cohen and Felson 1979; Beavon et al. 1994; Clarke 1994a, 1994b, 1996; Felson 1986, 1994). routine activities theory posits that crime occurs in specific locations based on the confluence of a number of important issues. First, there must be a suitable target, which may include individuals or property that is viewed as 'worth committing a criminal act against'. Next, there must be a motivated offender, which is often related to the relative depravation of criminal offenders in the form of poverty, unemployment, and other class related covariates. Lastly, there must be a lack of a capable guardian, which may be measured in a number of different ways, most often it is related to police strength and even to the ubiquity of ordinary citizens (Smith et al. 2000).

These two approaches have much in common, especially in terms of their sub-components which reduce each larger theory into smaller conceptual groupings. For instance, social disorganization can be directly broken down into the four sub-components listed above and then each of the components can be empirically tested in a nested fashion, within the larger theoretical grouping of variables associated with the framework. Likewise, routine activities theory can be broken down into the three sub-components listed above and tested in a similar manner. An example could include the urbanicity component of within the social disorganization framework, in which the population size and population density may be included in a reduced model to examine their effects sans the rest of the social disorganization variables. This makes testing the theories much more convenient and allows for the independent and isolated examination the effects of each.

However, the two theories are also quite different in that the social disorganization Theory focuses its attention on structure using a determinist approach, while the routine activities theory takes more of an agency approach concerned with the ability to decide when all three components make the opportunity for crime too good to resist. These differences highlight the age-old argument in much of social theory concerning the determinants of social actions, agency vs. structure. As with much of social theory, it can be assumed that the actual determinant of social action is a combination of structure and agency. These differences then allow for the integrated examination of the determinants, taking into account both the structure and agency determinants of social action, in this case offending.

The use of both of these theories together in some type of integrated fashion has increased recently as many researchers suggest that their integration may not only improve the state of knowledge concerning both theories independently but also the state of criminological theory as a whole (Kennedy and Forde 1990; Miethe and McDowall 1993; Miethe and Meier 1990, 1994; Miethe et al. 1987; Rountree et al. 1994; Sampson and Lauritsen 1990; Sampson and Wooldredge 1987; Simcha-Fagan 1986; Smith and Jarjoura 1989; Smith et al. 2000). These arguments tend to be primarily focused around the point that components which lead to criminal activity, from a criminal motivation standpoint, are linked to contextual situations in which the criminal acts based on an intersection of individual, place, and situation (Smith et al. 2000; Miethe and Meier 1994). This line of reasoning clearly identifies spatial locale as a central element of this integrated viewpoint.

These similarities and differences should allow for both an ease and exhaustiveness to the specification of the appropriate models concerned with the prediction of total, violent, and property crime for both the years of 1990 and 2000. As mentioned above, the sub-components of each allows for a neatly organized nested set of models within each theoretical framework, while the complementary nature of the two frameworks allow for an integrated and more realistic examination of the determinants from both a structural determinist and rational choice point of view.

From this specification and existing literature, it is also evident that the two theoretical frameworks contribute independently to the explanation of criminal activity and its likelihood of occurrence (Gottfredson et al. 1991; Sampson and Woolredge 1987; Simcha-Fagan and Schwartz 1986). For the coupling of the two, several propositions must be met (Meithe and McDowall 1993; Rountree et al 1994). "The fundamental hypothesis [proposition] is that the effects of individual characteristics change as a function of neighborhood characteristics. Specifically, within socially disorganized neighborhoods, a 'leveling' of the effects of individual components of risk may occur, presumably for reasons such as the prevalence of motivated offenders, short distances from crime target, and citizen disregard for alarms" (Smith et al. 2001).

In order to test the effects of both social disorganization Theory and routine activities theory, both independently and in integrated form, I have specified a set of equations shown below in a regression format. The analytic strategy employed here is a spatial regression approach aimed at controlling for the violation of OLS regression assumptions due to the autocorrelation evident in most data with spatial references (Anselin 1988). This is important because the use of these two theoretical frameworks elicits the examination of ecology as a central component to the social phenomena of crime, which is surprisingly often left unaccounted for in many of the more dominant criminological theories.

These non-ecological theories tend to deny the importance of physical attributes and give more attention to the social characteristics of those that commit crime. According to this approach, variation among places can be explained by the variations in the demographic characteristics (age, race, class, etc.) of individuals that occupy the given place (Gans 1962). Of importance to this study is not the lack of importance to such social/demographic characteristics, but instead the context in which place and the characteristics interact to produce an associated level of offending. Within criminology this has been coined “situational crime”, which is directly related to the efforts of local government to control crime in a given place known as “situational crime prevention” (Weisburd 1997; Loukaitou-Sideris et al. 2001).

There will be two basic sets of models, matching up to the above outlined theoretical frameworks through which this project is grounded, one for social disorganization and one for routine activities theory. The models will be specified in order to test the sub-components of each of the theoretical approaches on all three type-specific crime rates in a nested fashion. There will also be a third set of models aimed at examining the three type-specific crime rates via the fully-integrated theoretical model, consisting of both of the major ecological theories of interest in this study. The type-specific crime rates will be examined in both static form for both 1990 and 2000, and then in temporal fashion to examine the percent change in crime from 1990 – 2000.

In each case a series of interaction variables, computed with a place indicator variable, will be introduced in order to test the different effects of appropriate variables related to type of geography. These indicator variables are important to include in this analysis as they will allow for the explicit test of the differing effects of certain variables based on the type of geography. If in fact there are significant differences between the place and non-places in relation to a certain variable then not only will is show that the variable acts differently across rural and urban areas, but also that in controlling for all other variables, ecology matters in the examination and prediction of crime rates. In relation to the argument in the literature concerning the role and impact of geography on crime between those who back the ecological theories and those who disregard them, it will lend evidence to the fact that place must be taken into account and that while crime is related to social characteristics, they interact with the geographic area and do not act alone.

The models are laid out so that models 1-3 are concerned with the effects of the social disorganization while models 4-6 are concerned with the effects of the routine activities theory approach. Finally models 7-9 are the fully specified models containing all variables across both social disorganization and routine activities theory. This integrative approach should allow for the complete examination of crime by type (total, violent, and property) and the independent and integrated effects of both of the primary ecological frameworks for the examination of crime.

The first sets of models, models 1 – 3, are directly related to the explanation of the total crime rate, violent crime rate, and property crime rate, respectively. This analysis is undertaken via a series of nested models designed to empirically test the components of social disorganization theory while taking spatial proximity into account in the equation itself. There are four basic components within the theoretical perspective (outlined briefly above and in greater detail in the literature review): 1) urbanization, 2) racial/ethnic heterogeneity, 3) socioeconomic status, and 4) family disruption. All variables used in this model specification were based on the literature review (Land 1990, Land & Deane 1992, Land et al. 1991, Mandenka & Hill 1976, Wilson 1983, Boggs 1965, Schmid 1960a 1960b, Spector 1975, Danzinger 1976, Messner and Anselin 2004, Messner et al. 1999, Blau 1982, Crutchfield 2007, Ackerman 1998, Bloch 1949, Clinard 1944, Glaeser & Sacerdaote 1999, Paulson & Robinson 2004, Petee and Kowalski 1993, Wells & Weisheit 2004).

Within the following text, models 1-3 are denoted by an 'SD' to indicate their association with the social disorganization theoretical framework. This is to avoid reproducing each model three separate times, once for each type of crime (total, violent, and property) as they are introduced in this section. Likewise, models 4-6 are denoted with a 'RA' to indicate their association with the routine activities theoretical framework. Finally, models 7-9 are denoted with a 'FI' to denote their association with the fully specified composite ecological model.

Model SD1 in this first set of models (1-3) is designed to examine the urbanization component via the population size and population density. These two variables were used as they directly relate to the overall urbanization of an area with the total population size being a measure of pure size of place and population density being used as a measure to control for the total population relative to the geographic size of place. Arguably, these two variables are often thought to be synonymous with the concept of urbanization, making them logical choices as predictor variables for this component.

Regression Model: Social Disorganization/Urbanization Component

Model SD1 (Urbanization): Type-Specific Crime Rate (per 100k) = (5)
$B_0 + B_1$ *(Population Size)* $+ B_2$ *(Population Density)* $+ e$

Likewise, model SD2 is designed to test the racial/ethnic heterogeneity of an area via the percent black and the residential segregation of the area. The percent black in an area will give an approximate measure of the degree of racial heterogeneity as one would expect the population to much more homogeneous (white) as the percent black decreases. Also, a measure of residential segregation was used in order to account for the relative segregation of the races (black, white) via the dissimilarity index. This is important in the context of this theoretical framework as social disorganization, in general, is said to increase with the increased contact between 'unlike' groups (Paulson & Robinson 2004).

Regression Model: Social Disorganization/Racial-Ethnic Heterogeneity Component

Model SD2 (Racial/Ethnic Heterogeneity) Type-Specific Crime Rate (6)
(per 100k) $= B_0 + B_1$ *(Percent Black)* $+ B_2$ *(Residential Segregation)* $+ e$

Next, model SD3 is designed to examine the socioeconomic status component via the median family income, the percent with a college degree, and the percent unemployed. Obviously, all four of these variables measure some form of relative standing in regards to socioeconomic status. The median family income is a commonly used measure directly related to the economic affluence of an area. Similarly, the percent with a college degree is a proximate measure of an area's relative social standing based on the culturally significant measure of education. Next, the percent unemployed is a measure of community "wellness" based on the area's ability to employ individuals within the community.

Regression Model: Social Disorganization/Socioeconomic Status Component

Model SD3 (Socioeconomic Status): Type-Specific l Crime Rate (per 100k) (7)

$$= B_0 + B_1 \textit{(Median Family Income)} + B_2 \textit{(Percent with College Degree)} + B_4 \textit{(Percent Unemployed)} + e$$

Model SD4 is designed to test the family disruption component via the percent of all households that are female-headed, the percent divorced, and the percent of housing that is owner-occupied. Each of these variables aim to identifying varying levels of family stability, first via a measure of the percent of households that are female-headed. This measure allows for the identification of the degree to which the institution of the family within an area is affected by a lack of a two-parent stable household. Family disruption is also measured via the percent of the individuals within the community are divorced and finally, a measure of the percent of housing that is owner-occupied is used. All three of these measures proximately measure the relative level of family disruption with a higher percent female-headed households, higher percent divorced, and a lower percent of households owner-occupied all indicating higher levels of family disruption.

Regression Model: Social Disorganization/Family Disruption Component

$$\begin{aligned} &\textit{Model SD4 (Family Disruption): Type-Specific Crime Rate (per 100k)} \\ &\quad = B_0 + B_1 \textit{ (Percent Female-Headed Households)} \\ &\quad + B_2 \textit{ (Percent Divorced)} + B_3 \textit{ (Percent Housing Owner-Occupied)} + e \end{aligned} \tag{8}$$

Next, model SD5 is fully specified model designed to test the effect of all components of the social disorganization theoretical framework while controlling for all other variables related to the theoretical perspective. This will allow for a measure of the relative strength of each of the four components in the face of other components. An analysis and examination of standardized coefficients will further allow for a better understanding of the relative strength of each of them while also controlling for the spatial proximity of neighboring effects.

Regression Model: Social Disorganization/Fully Specified Model

$$\begin{aligned} &\textit{Model SD5 (Full Model): Type-Specific Crime Rate (per 100k)} \\ &\quad = B_0 + B_1 \textit{ (Percent Black)} + B_2 \textit{ (Median Family Income)} \\ &\quad + B_3 \textit{(Residential Segregation)} + B_4 \textit{ (Percent Below Poverty)} \\ &\quad + B_5 \textit{ (Percent Female-Headed Households)} + B_6 \textit{ (Population Size)} \\ &\quad + B_7 \textit{ (Population Density)} + B_8 \textit{ (Percent Unemployed)} \\ &\quad + B_9 \textit{ (Percent Divorced)} + B_{10} \textit{ (Percent with College Degree)} \\ &\quad + B_{11} \textit{ (Percent Housing Owner-Occupied)} + e \end{aligned} \tag{9}$$

Finally, model SD6 is designed to include all relevant control variables and relevant interaction terms related to the theoretical differences in rural and urban crime predictors. From the above literature review one would expect that the rate of crime would vary by percent black, the percent female-headed households, the median family income, the percent with a college degree, and the percent unemployed (Land 1990, Land & Deane 1992, Land et al. 1991, Mandenka & Hill 1976, Wilson 1983, Boggs 1965, Schmid 1960a 1960b, Spector 1975, Danzinger 1976, Messner and Anselin 2004, Messner et al. 1999, Blau 1982, Crutchfield 2007, Ackerman 1998, Bloch 1949, Clinard 1944, Glaeser & Sacerdaote 1999, Paulson & Robinson 2004, Petee and Kowalski 1993, Wells & Weisheit 2004). However, using an ecological approach, each of them are expected to be determinants of the type-specific crime rate in different magnitudes based on the type of geography and the proposition that social characteristics, such as the core demographics listed here, interplay with the environment to ultimately produce the given crime rate (see the Rural-Urban Crime Patterns in the literature review section above).

Regression Model: Social Disorganization/Fully Specified Model and Place-Level Interactions

$$\begin{aligned}
&\textit{Model SD6 (Place Indicator Variable) Type-Specific Crime Rate (per 100k)} \\
&\quad = B_0 + B_1 \textit{ (Percent Black)} + B_2 \textit{ (Median Family Income)} \\
&\quad + B_3 \textit{ (Residential Segregation)} + B_4 \textit{ (Percent Below Poverty)} \\
&\quad + B_5 \textit{ (Percent Female-Headed Households)} + B_6 \textit{ (Population Size)} \\
&\quad + B_7 \textit{ (Population Density)} + B_8 \textit{ (Percent Unemployed)} \\
&\quad + B_9 \textit{ (Percent Divorced)} + B_{10} \textit{ (Percent with College Degree)} \\
&\quad + B_{11} \textit{ (Percent Housing Owner Occupied)} + B_{12} \textit{ (Place Indicator)} \\
&\quad + B_{13} \textit{ (Percent Black*Place Indicator)} \\
&\quad + B_{14} \textit{ (Percent Female Headed Households * Place Indicator)} \\
&\quad + B_{15} \textit{ (Median Family Income * Place Indicator)} \\
&\quad + B_{16} \textit{ (Percent with College Degree * Place Indicator)} \\
&\quad + B_{17} \textit{ (Percent Unemployed * Place Indicator)} + e
\end{aligned} \tag{10}$$

The second sets of models (model 4 - 6) are directly related to the explanation of the total crime rate, violent crime rate, and property crime rate, respectively, in terms of the routine activities perspective. Like the first set of models, this analysis is undertaken via a series of nested models designed to examine the components of routine activities theory. There are three basic components within the theoretical perspective: 1) suitable target, 2) motivated offender, and 3) lack of a capable guardian. As before, the specification of models within this set are again designed to test each of the components independently and then again in a fully specified model.

Within the routine activities theory set of models, model RA1 tests the suitable target component of the framework via the use of three related variables. First, the median family income is used included as a measure of perceived suitability for crime, based on the likelihood, or lack of likelihood, of obtaining beneficial outcomes form committing a crime against someone. For example, area's of higher income are more likely than other to have higher rates of property crime due to the likelihood of the offender obtaining larger gains than in areas with lower average family incomes. Similarly, the percent college educated and the percent of home built prior to 1940 are included as visible measures of the likelihood of offending for the same reasons.

Regression Model: Routine Activities/Suitable Target Component

$$\textit{Model RA1 (Suitable Target): Type-Specific Crime Rate (per 100k)} \\ = B_0 + B_1 \textit{(Median Family Income)} + B_2 \textit{(Percent with College Degree)} \\ + B_3 \textit{(Percent Housing Pre-1940)} + e \tag{11}$$

Model RA2 is designed to test the motivated offender component of routine activities theory. The independent variables specified in this model are outlined above in the literature review as being linked to a higher likelihood of individual offending. The percent black, the percent in poverty, the percent female-headed households, and the percent unemployed are all predictors of a higher likelihood of offending at both the individual and structural level (Paulson and Robinson 2004). Also related, the percent of the population under the age of 18 and the percent of the population between the ages of 18-24 are both included as predictors of offending via the motivated offender's component of the routine activities theory. These last two variables are included based on the aging out of crime theory, which posits that as individuals move out of certain age groups they are much less likely to commit crimes of all types.

Regression Model: Routine Activities/Motivated Offender Component

$$\textit{Model RA2 (Motivated Offender): Type-Specific Crime Rate (per 100k)} \\ = B_0 + B_1 \textit{(Percent Black)} + B_2 \textit{(Percent Below Poverty)} \\ + B_3 \textit{(Percent Female-Headed Households)} \\ + B_4 \textit{(Percent Unemployed)} + B_5 \textit{(Percent Population Under Age 18)} \\ + B_6 \textit{(Percent Population Between 18-24)} + e \tag{12}$$

Next, model RA3 is concerned with the lack of a capable guardian component related to the routine activities theory. Again, this component is related to the individual rational choice related to offending and the impact that a perceived capable guardian would on affecting that choice. The population size and population density are both included as measures of civilian guardians within the community. From the literature review above it seems that the effect of population size and density may in fact raise the crime rate as they increase, however the measures are also often mentioned as indicators of capable guardians (Paulson and Robinson 2004). Next, the rate of police officers per 1,000 residents and the rate of police force employees per 1,000 residents were included as a more formal measure of capable guardians.

Regression Model: Routine Activities/Lack of Capable Guardian Component.

$$\begin{aligned} &\textit{Model RA3 (Lack of Capable Guardian): Type-Specific Crime Rate (per 100k)} \\ &\quad = B_0 + B_1 \textit{ (Total Population)} + B_2 \textit{ (Population Density)} \\ &\quad + B_3 \textit{ (Rate of Police Officers per 1k)} + e \end{aligned} \tag{13}$$

Lastly, model RA4 is specified to test the entire routine activity theory framework with all components as controls for all other indicators. The model will again, as with the above social disorganization models, be examined via the standardized regression coefficients so that relative effects may be measured across all variables. Also similar to the earlier specifications, a full model plus controls and all relevant demographic variables with the place indicator interaction variables will also be included in model RA5. This will, again, allow for the examination of criminal offending at an ecological level while examining criminal activity across the different geographies.

Regression Model: Routine Activities/Fully Specified Model.

$$\begin{aligned}
&\textit{Model RA4 (Full R.A.T. Model) Type-Specific Crime Rate (per 100k)}\\
&\quad = B_0 + B_1 \textit{ (Percent Black)} + B_2 \textit{ (Median Family Income)}\\
&\quad + B_3 \textit{ (Percent Below Poverty)} + B_4 \textit{ (Percent Female-Headed Households)}\\
&\quad + B_5 \textit{ (Percent Unemployed)} + B_6 \textit{ (Percent with College Degree)}\\
&\quad + B_7 \textit{ (Percent Housing Pre-1940)} + B_8 \textit{ (Percent Population Under Age 18)}\\
&\quad + B_9 \textit{ (Percent Population Between 18-24)} + B_{10} \textit{ (Total Population)}\\
&\quad + B_{11} \textit{ (Population Density)} + \textit{(Rate of Police Officers per 1k)} + e
\end{aligned} \tag{14}$$

Regression Model: Routine Activities/Fully Specified Model Plus Place-Level Interactions.

$$\begin{aligned}
&\textit{Model RA5 (Place Indicator): Specific Crime Rate (per 100k)}\\
&\quad = B_0 + B_1 \textit{ (Percent Black)} + B_2 \textit{ (Median Family Income)}\\
&\quad + B_3 \textit{ (Percent Below Poverty)} + B_4 \textit{ (Percent Female-Headed Households)}\\
&\quad + B_5 \textit{ (Percent Unemployed)} + B_6 \textit{ (Percent with College Degree)}\\
&\quad + B_7 \textit{ (Percent Housing Pre-1940)} + B_8 \textit{ (Percent Population Under Age 18)}\\
&\quad + B_9 \textit{ (Percent Population Between 18-24)} + B_{10} \textit{ (Total Population)}\\
&\quad + B_{11} \textit{ (Population Density)} + B_{12} \textit{ (Percent Black*Place Indicator)}\\
&\quad + B_{13} \textit{ (Percent Female Headed Households * Place Indicator)}\\
&\quad + B_{14} \textit{ (Median Family Income * Place Indicator)}\\
&\quad + B_{15} \textit{ (Percent with College Degree * Place Indicator)}\\
&\quad + B_{16} \textit{ (Percent Unemployed * Place Indicator)} + e
\end{aligned} \tag{15}$$

As mentioned above, the social disorganization theoretical framework is interested in both the existing social structure and changes within the social structure over a given period of time (Paulson and Robinson 2004). As this is an ecological examination of crime it is appropriate to examine such structural conditions. However, when solely examining the structural variability one neglects to understand the individual agency involved in offending. The routine activities theory framework takes into account such individual rational choice within the greater context of a given structure (Paulson and Robinson 2004). It is evident through the literature review that the act of offending is both structural and individual in terms of predicting the occurrence of criminal activity.

However, what we do not know is the ability and power of each model independently and controlling for other theoretical frameworks, or given a particular level of geography. For example, does routine activities theory hold similarly in both the core areas, such as places, and in periphery areas, such as non-places and does the theory hold in the face of structural determinants, such as those controlled for in the social disorganization set of models? The literature review points out that the two ecological theories; above as the first two sets of models, used in this project are complementary and do adequately cover the weak areas of the alternative set of models (Smith et al. 2001).

Based on this point, the final set of models, numbers 7-9 (models FI) are aimed at test the integrated effects of all independent variables specified in models 1 – 6, again for the total, violent, and property crime rates. This desegregation of crime into type-specific crime, throughout this analysis, is deemed to be important here as it addresses one of the fundamental issues in criminology, offending of differing crime types occur at differing magnitudes based on the urbanicity or reality of the area of interest (Ackerman 1998, 2001; Crutchfield 2007; Wilson 1983; Mandenka and Hill 1976; Messner and Anselin 2004; Messner et al. 1999; Blau and Blau 1982; Spector 1975; Danzinger 1976). This approach will independently allow for the testing of the structurally centered social disorganization theoretical framework, the agency based routine activities theoretical framework, and the integrative structure and agency joint model, shown below in model FI1, while also including the place indicator in order to continue to examine the differing effects of each of these theoretical frameworks and their determinants across the two different geographies used in this project, shown below in model FI2.

Regression Model: Integrated Social Disorganization and Routine Activities Model.

Model FI1 (Fully Specified Integrated Ecological Model): Type-Specific Crime

$$\begin{aligned}
&\textit{Rate (per 100k)} = B_0 + B_1\ \textit{(Percent Black)} + B_2\ \textit{(Median Family Income)}\\
&+ B_3\ \textit{(Residential Segregation)} + B_4\ \textit{(Percent Below Poverty)}\\
&+ B_5\ \textit{(Percent Female Headed Households)} + B_6\ \textit{(Population Size)}\\
&+ B_7\ \textit{(Population Density)} + B_8\ \textit{(Percent Unemployed)}\\
&+ B_9\ \textit{(Percent Divorced)} + B_{10}\ \textit{(Percent with College Degree)}\\
&+ B_{11}\ \textit{(Percent Housing Owner-Occupied)} + B_{12}\ \textit{(Percent Housing pre-1940)}\\
&+ B_{13}\ \textit{(Percent Population Under 18)} + B_{14}\ \textit{(Percent Population 18-24)}\\
&+ B_{15}\ \textit{(Percent Rate of Police Officers per 1k)} + + B_{16}\ \textit{(Metro Status)}\\
&+ B_{17}\ \textit{(U.S. Census Region)} + e
\end{aligned} \tag{16}$$

Regression Model: Integrated Social Disorganization and Routine Activities Model Plus Place-Level Interactions.

Model FI2 (Fully Specified Integrated Ecological Model): Type-Specific Crime

$$\begin{aligned}
&\textit{Rate (per 100k)} = B_0 + B_1\ \textit{(Percent Black)} + B_2\ \textit{(Median Family Income)}\\
&+ B_3\ \textit{(Residential Segregation)} + B_4\ \textit{(Percent Below Poverty)}\\
&+ B_5\ \textit{(Percent Female Headed Households)} + B_6\ \textit{(Population Size)}\\
&+ B_7\ \textit{(Population Density)} + B_8\ \textit{(Percent Unemployed)}\\
&+ B_9\ \textit{(Percent Divorced)} + B_{10}\ \textit{(Percent with College Degree)}\\
&+ B_{11}\ \textit{(Percent Housing Owner-Occupied)} + B_{12}\ \textit{(Percent Housing pre-1940)}\\
&+ B_{13}\ \textit{(Percent Population Under 18)} + B_{14}\ \textit{(Percent Population 18-24)}\\
&+ B_{15}\ \textit{(Percent Rate of Police Officers per 1k)} + B_{16}\ \textit{(Metro Status)}\\
&+ B_{17}\ \textit{(U.S. Census Region)} + B_{18}\ \textit{(Percent Black*Place Indicator)}\\
&+ B_{19}\ \textit{(Percent Female Headed Households * Place Indicator)}\\
&+ B_{21}\ \textit{(Median Family Income * Place Indicator)}\\
&+ B_{20}\ \textit{(Percent with College Degree * Place Indicator)}\\
&+ B_{21}\ \textit{(Percent Unemployed * Place Indicator)} + e
\end{aligned} \tag{17}$$

This concludes the regression models that will be implemented in the predictive analytic phase. Of course, depending on the results of the ESDA in the descriptive phase of the analysis, each of these models may also include another terms in the form of a spatial lag or error term. Again, these will only appropriate if the ESDA results show a significant non-random pattern, associated with the dependent variable, across geographic space. In that case, as mentioned above, it is important to explicitly control for the crime rate of neighboring geographic units in order to overcome the violation of correlated error terms, from which biased and unreliable parameter estimates may be obtained.

Exploratory Analysis of Spatial Diffusion

The final phase of the analysis is interested in detection and identification of the spatial mobility of crime over the study period, 1990 – 2000. While the first and second phase of the analysis both implicitly tied temporal change into the model specifications, this section is solely dedicated to the examination of type-specific crime rates in both space and time. Of note, this is also an exploratory phase as the detection of geographic rates, incidence and clusters, which tie time and space together are few and far between. In fact there is a lack of precedence using such analyses, net the work of Kulldorf (2001), Rogerson (2001), Lazarus et al. (2002), Mostashari et al. (2003), Cohen and Tita (1999), among a few others.

For this reason, this section is both the hardest to specify and potentially the largest methodological contribution to the field of sociology from this study.

As reviewed above, Cohen and Tita (1999) used the univariate LISA statistic at two different time points to identify the diffusion of crime over both geographic and temporal units. The current examination hopes to further this method for the detection of the mobility of criminological offending over a temporal period by implementing the bivariate LISA statistic. As opposed to the univariate LISA, which tests spatial dependence related to one variable and the neighbor's average value on that same variable, the bivariate LISA allows for the examination of one variable at location *i* against the average neighborhood score of a second variable (Anselin 2003).

Building upon the innovative work by Cohen and Tita (1999) this analysis will examine the spatial mobility of crime as follows:

Computation of Global Bivariate Moran's I Coefficient.

$$I = \left(\frac{1}{s2}\right)\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_{ij}(Yi-\overline{Y})(Xj-\overline{X})}{\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_{ij}} \tag{18}$$

Where:

$$s2 = \frac{1}{N}\sum_{i=1}^{N}(Yi-\overline{Y})\wedge 2$$

As one can see the equation is very similar to the equation for the univariate LISA list above in the descriptive phase of this analysis. However, as you can see the *Yj* has been replaced with the *Xj*. Within this analysis the *Yi* will be the type-specific crime rate at T1 (1990), while the *Xj* will be the neighborhood average type-specific rate at T2 (2000).

This equation, of course, is akin to the Pearson Correlation Coefficient, as mentioned earlier, with a simple weight indicator (ω_{ij}). The measure of spatial dependence is equal to a measure of variation in the area unit specific rate and the overall mean rate (s^2) multiplied by the neighbor weight indicator (ω_{ij}) times the product of each unit's (*Yi*) proportion of crime at t1 minus the overall mean of the same variable and each average neighborhood's (*Xj*) percent change in the proportion of crime accounted for in the county minus the overall mean then divided again by the weight indicator and summed across all units (i)and across all neighborhoods (j) for both the denominator and the numerator (Waller and Gotway 2004; Anselin 1995).

Once spatial dependence is identified using the bivariate global Moran's I approach, a permutations significance will be employed, again at 999 permutations (Waller and Gotway 2004). Next, local areas of significance will be detected via the bivariate LISA statistic. The LISA statistic provides a significance value for each case based on local neighborhood deviations from the overall expected rates of crime (Waller and Gotway 2004). The equation for the bivariate LISA is as follows:

Computation of Bivariate Local Indicator of Spatial Association Coefficients

$$Ii = \sum_{j=1}^{N} \omega ij(Yi - \overline{Y})(Xj - \overline{X}) \qquad (19)$$

From this equation you can see that the random variable *Ii* is equal the weight indicator multiplied by the product of the type-specific crime rate in 1990 (*Yi*) and the neighborhood average type-specific crime rate in 2000 (*Xj*). Simply put the LISA value for a given location is simply equal to the relationship between the two variables of interest (correlation) multiplied by the weight indicator (one if considered a neighbor, zero if otherwise). This approach will then allow for the examination of pockets of significant spatial mobility of crime within each county.

This concludes the model specification and the larger Methodology chapter of this project. Following this section there are three chapters of analysis, primarily for organizational purposes, will be presented in the order they were laid out above. Chapter 4 will present the results of the statistical and spatial description of the variables used in the study. Within this section tests for spatial dependence and differences in means across limited variable categories will be examined. In Chapter 5, the results from modeling to predict type specific crime rates will be reported, with attention given to model selection procedures including the Lagrange Multiplier Test. Finally, in Chapter 6 the results from the exploratory examination of the spatial mobility of type-specific crime rates will be reported.

CHAPTER IV

DESCRIPTION OF REPORTED CRIME IN SUB-COUNTY GEOGRAPHIES, 1990 - 2000

Statistical Description

The initial phase of this analysis involves the statistical description of all dependent and independent variables pertinent to this project. Statistically, this analysis will examine the normality, the statistical description, and covariation of all dependent and independent variables. First, each type-specific crime rate related dependent variable will be examined via Q-Q plots in order to determine whether the distribution meets normality expectations and alternative transformations will be identified as needed [cite here]. Next, the distribution of all independent variables will be statistically examined and again, appropriate measures will be taken to ensure that each meets all assumptions. Finally, the covariation of all independent variables will be examined in order to identify potential cases of multicolinearity. These initial results will allow for the proper measures to be taken to assure that all assumptions are met concerning the subsequent modeling procedures implemented in latter in this chapter and in the chapters that follow.

It is important to emphasize again that one of the primary contributions of this dissertation is the introduction of a sub-county description, predictive examination, and modeling of spatial mobility and diffusion processes of reported crime at a national scale. Prior to this study, the examination of reported crime *at a national scale* has always been undertaken at a county-level while examinations at the sub-county level concerned themselves with small-scale geographic areas. It is argued throughout the literature, and continued further here, that due to the internal heterogeneity of counties, a sub-county examination may be able to uncover processes undetectable in previous analyses (Land and Deane 1992; Messner et al. 1999; Messner and Anselin 2004).

To directly test the thesis that there is significant within-county variation, a one-way ANOVA was used to examine the within and between county variance in terms of all three type-specific crime rates at both points in time (Ott and Longnecker 2000). This will allow for the examination of the amount of variation accounted for by simply being classified by county type. The results show that while there are significant variations between counties in all six dependent variables, there is also a significant amount of variation left unexplained by the county differences within each county. The focus in this study, for instance, is on the spatial spread of crime from cities (places) to less densely populated localities (non-places). Since only between forty and forty-three percent of the variation can be accounted for the county level classification, and there is a significant amount of documented heterogeneity within categories, it is important to continue this sub-county analysis and try to better understand where this variation occurs geographically[6].

Description and Distribution of Criminal Offending

Before any further analyses can take place, it is important to first take some time to statistically explore the data that will be used (Tukey 1977; Ott and Longnecker 2000; Tabachnik and Fidel 2006). The results in figure 7 illustrate the examination of normality concerning the type-specific crime rates for 1990, using Q-Q plots (Ott and Longnecker 2000). It is evident from the top row, examining the raw rate, that the data for all three type-specific crime types are not normally distributed, if they were normal there would be a diagonal line from the origin, where the x and y axis join, to the directly opposite corner and all of the data points would closely follow that line (Ott and Longnecker 2000). A number of transformations were examined, with the natural log proving to produce the most normal distribution for all three of the variables. From the bottom row, one can see the greatly improved results from this transformation. Results from

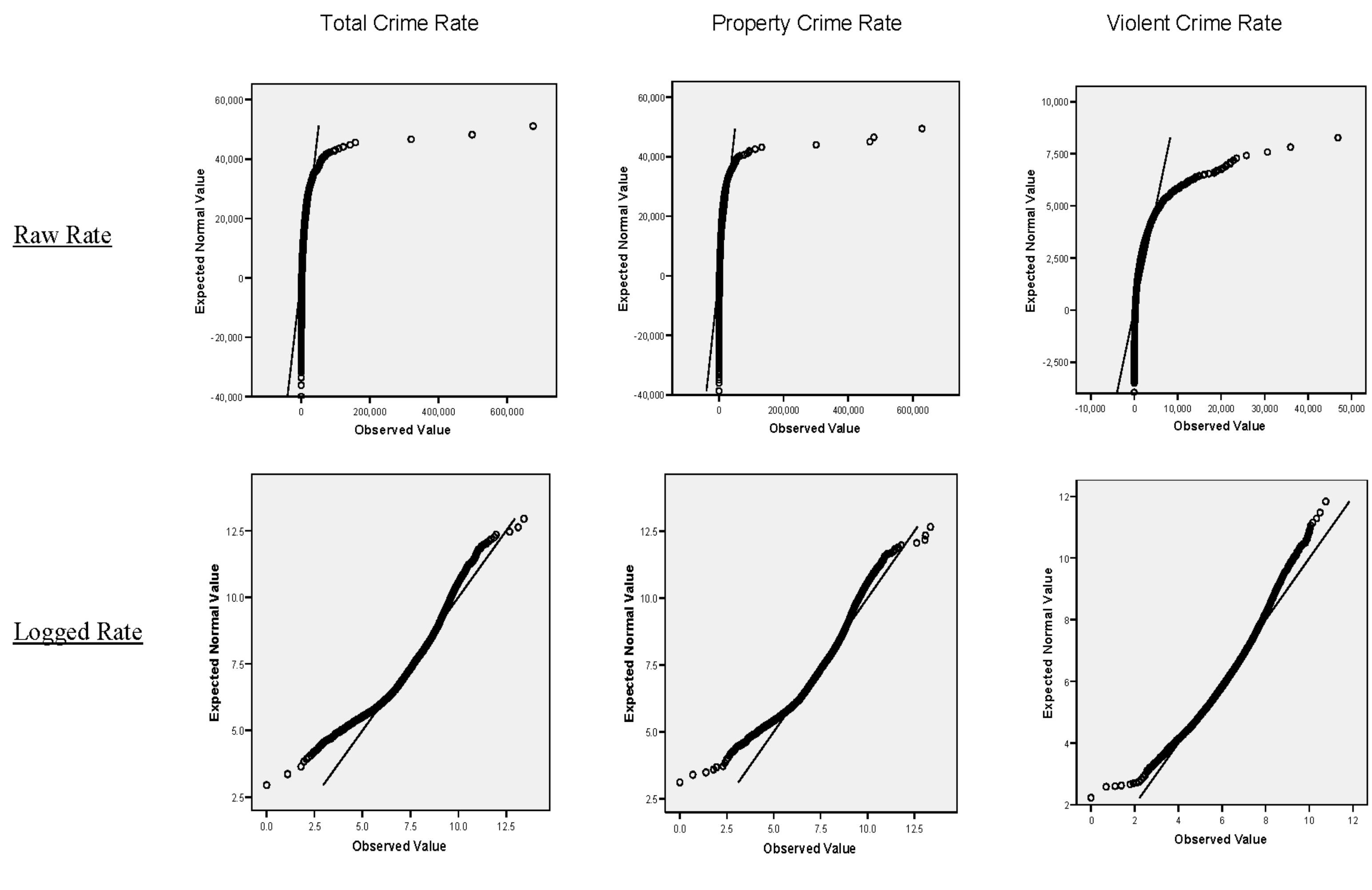


Figure 7. Q-Q Plot for Normality of Dependent Variables, 1990

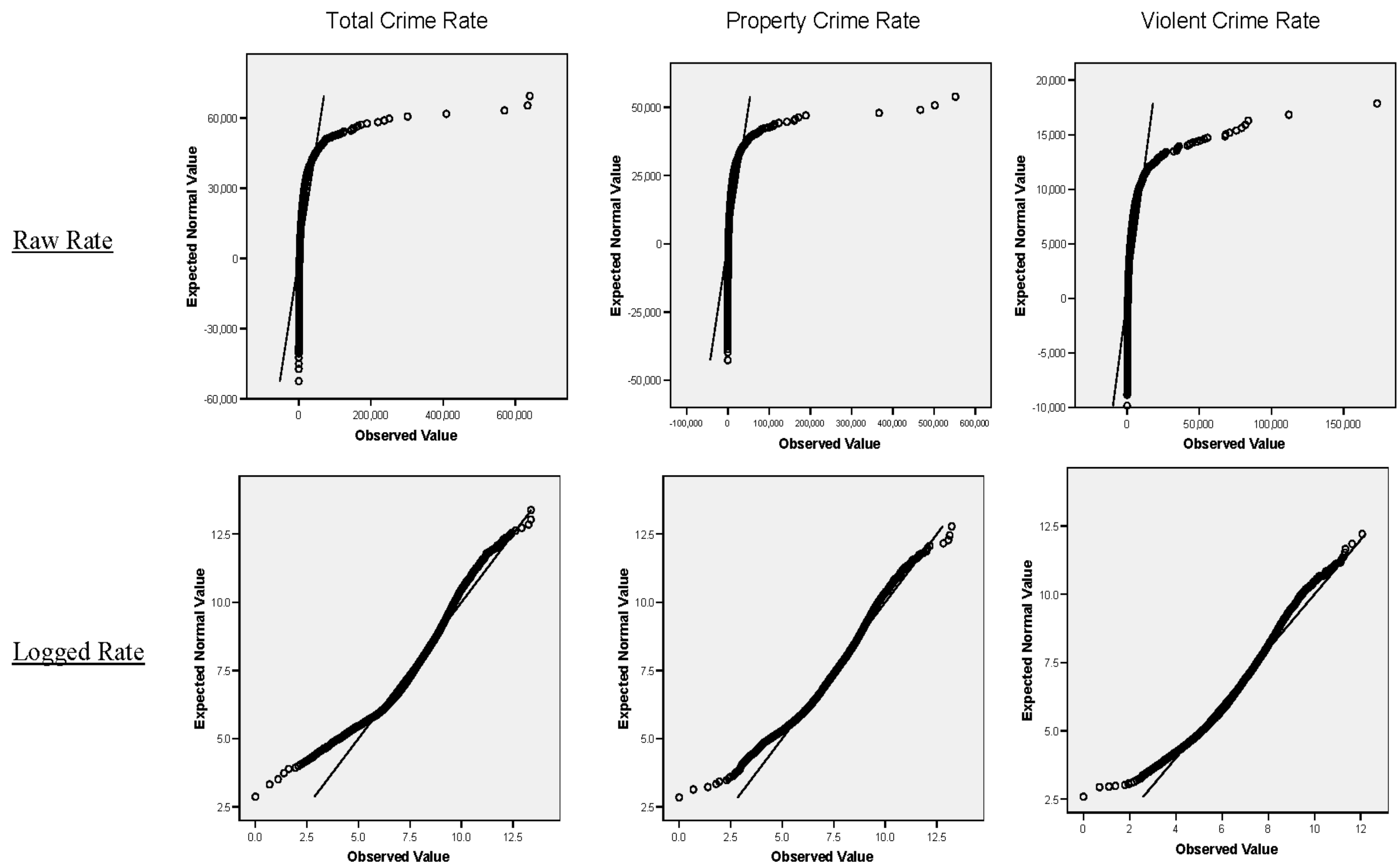


Figure 8. Q-Q Plot for Normality of Dependent Variables, 2000

figure 8 concerning the 2000 data, are similar, as the natural log transformation again proved to be the most normal distribution of all those examined.

Once the dependent variables were transformed to be reasonably close to normality to ensure no statistical issues, the '*gladder*' (StataCorp 2005b) procedure in Stata was used on all independent variables found to be non-normal by the initial examination of the kurtosis and skewness of each variable. In order to ascertain the most appropriate transformation, the command returns a 3x3 lattice of nine separate histograms, from which it is easy to identify the most normal for the purpose of variable transformation (StataCorp 2005b). The nine transformations examined included the raw variable, the squared variable, the cubed variable, the square root of the variable, the natural log of the variable, the reciprocal of the variable, the reciprocal root of the variable, the reciprocal square of the variable, and the reciprocal cube of the variable (StataCorp 2005).

Ultimately, the examination resulted in the transformation of the per capita income variable via the natural log in both 1990 and 2000, the overall population size being logged in both 1990 and 2000, the population density being logged in both 1990 and 2000, the square root being taken of the percent divorced in only 2000 (the raw variable was approximately normal in 1990), the square root being taken of the percent with a college bachelor's degree in both 1990 and 2000, and the number of officers per one thousand residents being logged in both

1990 and 2000. These variables and all normal, non-transformed, variables were included in table 2 where the mean and standard deviation of each was examined.

From the table, it is possible to see the mean values and standard deviations for all variables across both time periods used in this study. From the left column, the 1990 values are examined while the 2000 values are in the right hand column. As shown in the table, the average percent black in 1990 was lower than it was in 2000, while the average per-capita income was higher in 2000 than in 1990. Also, the residential segregation score was exactly the same across both time points, the percent in poverty was slightly lower in 2000 than 1990, as was the percent of female headed households. Both the average population size and the average population density were relatively similar across both 1990 and 2000, while the percent unemployed was slightly higher in 1990 than 2000. In terms of housing characteristics, the percent of housing owner-occupied was higher in 2000 than 1990 and the percent of housing pre-1940 was lower in 2000 than 1990. Finally, the percent of the population under eighteen and the percent between the ages of eighteen and twenty-five were relatively the same, while the percent of officers per one thousand individuals in the community was lower in 2000 than it was in 1990.

Table 2. Descriptive Statistics of Theoretically Appropriate Independent Variables

Independent Variables	1990 Mean	1990 Standard Deviation	2000 Mean	2000 Standard Deviation
Percent Black	8.66	14.92	9.35	15.85
(LN) Per Capita Income	9.38	0.33	9.76	0.33
Residential Segregation	0.44	0.29	0.44	0.27
Percent Below Poverty	14.58	8.63	13.23	7.57
Percent Female Headed Households	14.86	7.10	10.54	5.10
(LN) Population Size	9.13	1.46	9.05	1.40
(LN) Populaiton Density (per square mile)	5.87	2.25	5.85	2.23
Percent Unemployed	2.96	1.30	2.75	1.58
Percent Divorced	6.27	2.15	--	--
(SQRT) Percent Divorced	--	--	2.77	0.43
(SQRT) Percent College Degree (BA)	3.92	1.46	3.50	1.24
Percent of Housing Owner-Occupied	46.32	13.18	60.20	13.35
Percent Housing Pre-1940	22.49	16.87	19.95	15.64
Percent of Population Under the Age of 18	25.96	4.90	25.27	4.55
Percent of Popualtion Between the Ages of 18-24	9.69	5.43	9.26	5.53
(LN) Police Strength (per 1k)	0.69	0.78	0.37	1.13

Table 3. Descriptive Statistics of Theoretically Appropriate Independent Variables by Geographic Identifier (Place vs. Non-Place)

	Place		Non-Place Territory (NPT)	
	1990	2000	1990	2000
Independent Variables	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Percent Black	9.11 (15.36)	10.00 (16.60)	7.90 (14.08)	8.21 (14.41)
(LN) Per Capita Income	9.42 (0.36)	9.78 (0.37)	9.30 (0.23)	9.73 (0.24)
Residential Segregation	0.37 (0.28)	0.35 (0.26)	0.57 (0.27)	0.58 (0.22)
Percent Below Poverty	13.98 (8.89)	13.28 (8.13)	15.62 (8.04)	13.16 (6.48)
Percent Female Headed Households	11.75 (5.29)	16.73 (7.35)	8.44 (3.97)	11.64 (5.29)
(LN) Population Size	8.68 (1.38)	8.61 (1.30)	9.91 (1.25)	9.82 (1.24)
(LN) Populaiton Density (per square mile)	7.25 (1.09)	7.17 (1.21)	3.46 (1.61)	3.57 (1.66)
Percent Unemployed	3.01 (1.39)	2.87 (1.78)	2.88 (1.23)	2.52 (1.14)
Percent Divorced	6.79 (2.30)	--	5.37 (1.46)	--
(SQRT) Percent Divorced	--	2.83 (0.47)	--	2.66 (0.33)
(SQRT) Percent College Degree (BA)	4.04 (1.62)	3.64 (1.41)	3.73 (1.13)	3.27 (0.82)
Percent of Housing Owner-Occupied	49.86 (13.32)	58.08 (13.67)	40.18 (10.40)	63.92 (11.90)
Percent Housing Pre-1940	23.49 (18.41)	21.05 (16.98)	20.76 (13.67)	18.06 (12.82)
Percent of Population Under the Age of 18	25.18 (5.37)	25.03 (5.10)	27.23 (3.62)	25.71 (3.34)
Percent of Popualtion Between the Ages of 18-24	10.26 (6.35)	9.82 (6.53)	8.71 (3.06)	8.29 (2.90)
(LN) Police Strength (per 1k)	1.00 (0.66)	0.32 (1.11)	0.16 (0.67)	-0.45 (1.15)

While this general description of the independent variables allows for a broad overview of the variables across the U.S., it does not allow us to examine the variables across the primary geography of interest in this study, place and non-place territory (NPT). Table 3 is the replica of table two; however, this time the variable description is examined across the place-level geography, which is the primary delineation of the units of analysis in this study. This examination allows for a deeper insight to the understanding of the distribution of these independent variables across and between places and non-places.

From table 3, one can see that the percent black living in an area is, on average, higher in places than it is in non-places. This is also the case for per-capita income, the percent of all households that are female headed, and the percent unemployed. The percent in poverty is slightly higher in the non-place territory than it is in places, which is also the case for the level of residential segregation. In terms of the population distribution, on average non-places have a slightly higher population but it is important to remember that these areas are also much larger in terms of square mileage (see figure 1) and the population density of places dwarf that of non-places upon further examination. Lastly, the percent of the population under eighteen is similar across both geographies, the percent of population between the ages of eighteen and twenty-four is slightly higher in places, and the rate of officers per one thousand individuals is higher in places than non-places.

Covariation among the Determinants of Criminal Offending

Now that both the dependent and independent variables have been examined in regards to the normality of their distribution and the independent variable have been described, including comparisons by the level of geography, the next phase of the statistical description examines bivariate relationships between the independent variables. This examination is aimed at testing for potential signs of multicolinearity. This examination makes use of the Pearson correlation coefficient for both the 1990 and 2000 sets of variables (Ott and Longnecker 2000).

Table 4 contains the results of the bivariate correlations for the set of independent variables in 1990. For these correlations, there does not seem to be any serious issues with colinearity, with the largest of all associations being between the percent below poverty and the percent of all female-headed households with a coefficient of .726. Other associations of interest in table 4 include the relationship between percent black and residential segregation (.558), the income per-capita and the population size (.685), the percent female headed households and the population size (.519), and the percent unemployed with the population size (.453). In general, these results show that while there are moderate levels of correlation between some of the independent variable, multicolinearity does not seem to be an issue.

Similar results were obtained from the same examination of the variables for the year of 2000. These results are displayed in table 5 and again show no serious issues with colinearity. This time the largest association is again between the percent below poverty and the percent of households that are female-headed with a coefficient of .651. Other associations of interest are again similar to the relationships between the 1990 variables including, the relationship between percent black and residential segregation (.524), the income per-capita and the population size (.647), the percent female-headed households and the population size (.541), and the percent unemployed with the population size (.446). From the results of both the 1990 and 2000 pair-wise relationships displayed in tables 4 and 5 respectively, it is evident that no serious issues of colinearity exist on the basis of zero-order correlation values. Additional results, implementing a principal components factor analysis approach, again show that moderate levels of shared variation exist, however to confirm that multicolinearity does not exist it should be further examined in subsequent predictive analyses[7].

From this initial statistical description, both the dependent and independent variables have been evaluated for normality, with the non-normal

Table 4. Bivariate Correlation Between all Theoretically Appropriate Independent Variables, 1990

Independent Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
[1] Percent Black	1	.061**	.558**	.161**	-.113**	-.033**	-.067**	.049**	-0.01	-.132**	-.079**	-.267**	.045**	.133**	-.437**
[2] (LN) Per Capita Income	--	1	-.045**	-.228**	.411**	.685**	.072**	.240**	.046**	-.152**	-.091**	-.213**	.092**	.109**	.160**
[3] Residential Segregation	--	--	1	.055**	-.032**	-.084**	-.169**	.041**	-.041**	-0.01	-.090**	-.095**	.024**	0.01	-.362**
[4] Percent Below Poverty	--	--	--	1	.726**	-.309**	.298**	-.425**	.038**	.547**	.374**	-.043**	-.381**	-.128**	.123**
[5] Percent Female Headed Households	--	--	--	--	1	.519**	-.186**	.506**	.039**	-.291**	-.406**	-.071**	.298**	.113**	.024**
[6] (LN) Population Size	--	--	--	--	--	1	.400**	.453**	.403**	-.192**	-.120**	-0.02	.034**	.179**	.305**
[7] (LN) Populaiton Density (per square mile)	--	--	--	--	--	--	1	.081**	.353**	.041**	.420**	.068**	-.276**	.214**	.419**
[8] Percent Unemployed	--	--	--	--	--	--	--	1	.209**	-.307**	-.230**	-.047**	.202**	.134**	0.02
[9] Percent Divorced	--	--	--	--	--	--	--	--	1	-0.01	-.144**	-.076**	-.230**	-.036**	.286**
[10] (SQRT) Percent College Degree (BA)	--	--	--	--	--	--	--	--	--	1	.029**	.164**	-.337**	.025**	.254**
[11] Percent of Housing Owner-Occupied	--	--	--	--	--	--	--	--	--	--	1	.029**	0.01	-.146**	.116**
[12] Percent Housing Pre-1940	--	--	--	--	--	--	--	--	--	--	--	1	-.168**	-.058**	0.01
[13] Percent of Population Under the Age of 18	--	--	--	--	--	--	--	--	--	--	--	--	1	-.276**	-.179**
[14] Percent of Popualtion Between the Ages of 18-24	--	--	--	--	--	--	--	--	--	--	--	--	--	1	.055**
[15] (LN) Police Strength (per 1k)	--	--	--	--	--	--	--	--	--	--	--	--	--	--	1

** Correlation Significant at < .001 level

Table 5. Bivariate Correlation Between all Theoretically Appropriate Independent Variables, 2000

Independent Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
[1] Percent Black	1	.061**	.524**	.190**	-.067**	-.037**	-.039**	.038**	.023**	0.00	.104**	-.231**	0.01	.093**	-.146**
[2] (LN) Per Capita Income	--	1	-.098**	-.187**	.447**	.647**	.091**	.236**	.071**	-.157**	-.161**	-.224**	.078**	.110**	.045**
[3] Residential Segregation	--	--	1	.109**	-.059**	-.177**	-.224**	-0.02	-0.02	-0.02	.121**	-.033**	-0.01	-.028**	-.053**
[4] Percent Below Poverty	--	--	--	1	.651**	-.411**	.204**	-.347**	0.01	.626**	.372**	0.00	-.300**	-.222**	-.037**
[5] Percent Female Headed Households	--	--	--	--	1	.541**	-.071**	.446**	.123**	-.400**	-.449**	-.110**	.208**	.228**	.090**
[6] (LN) Population Size	--	--	--	--	--	1	.369**	.351**	.235**	-.218**	-.324**	-.114**	.256**	.122**	.052**
[7] (LN) Populaiton Density (per square mile)	--	--	--	--	--	--	1	.128**	.217**	.177**	-.137**	.069**	-.114**	.180**	.033**
[8] Percent Unemployed	--	--	--	--	--	--	--	1	.059**	-.219**	-.316**	-.044**	0.02	.440**	.042**
[9] (SQRT) Percent Divorced	--	--	--	--	--	--	--	--	1	-.101**	-.234**	-.036**	-.230**	-.098**	0.01
[10] (SQRT) Percent College Degree (BA)	--	--	--	--	--	--	--	--	--	1	-.030**	.028**	-.291**	-.057**	0.02
[11] Percent of Housing Owner-Occupied	--	--	--	--	--	--	--	--	--	--	1	-.061**	.123**	-.295**	-.111**
[12] Percent Housing Pre-1940	--	--	--	--	--	--	--	--	--	--	--	1	-.154**	-.037**	-.077**
[13] Percent of Population Under the Age of 18	--	--	--	--	--	--	--	--	--	--	--	--	1	-.265**	0.00
[14] Percent of Popualtion Between the Ages of 18-24	--	--	--	--	--	--	--	--	--	--	--	--	--	1	.026*
[15] (LN) Police Strength (per 1k)	--	--	--	--	--	--	--	--	--	--	--	--	--	--	1

** Correlation Significant at < .001 level

* Correlation Significant at < .005 level

variables being transformed to the most optimal approximation identified. All independent variables have been statistically described, via measures of central tendency and variation, across all elements in the entire study region and between the place-level geography in tables 2 and 3. Later in this chapter, the type-specific crime rates as dependent variables will be examined across both geographic levels and over time through a more formal test of mean differences involving tests of statistical significance. Next, this chapter will move from the traditional Exploratory Data Analysis (EDA) (Tukey 1977) used in this section to Exploratory Spatial Data Analysis (ESDA) (Anselin 1988, 1995) for examining the data's potential non-random variation across geographic space, particularly for places and non-place territories.

Spatial Description

Exploratory Spatial Data Analysis is important in this study primarily due to the fact that the theories and data are explicitly tied to space. Theoretically, this dissertation makes use of two of the most prominent ecological theories in the field of criminology, social disorganization and routine activities theory. The fact hat both of these two theories are grounded in the ecological 'space' of offending behavior elicits the need for spatial data analysis. In addition, the methodology involved in developing the geographic units of analysis for this project further underscores the appropriateness of exploratory spatial data analysis in order to identify potential underlying spatial process associated with both the theoretical prediction of offending within and between the new place-level geographies (i.e., places and the remaining out-in-the-county, or non-place, territories).

Spatial Distribution of Raw Crime Rates

The first phase of the exploratory spatial analysis involves the visualization of the simple spatial distribution of type-specific crimes across the study region. For this phase, the logged rates of all three crime types were mapped in psudeo-natural breaks with a standardized legend in order to try and identify spatial patterns associated with each of the dependent variables. Each of the type-specific crime rates were also mapped separately for both points in time in order to assess any potential changes in the geographic distribution of the variables over the time period. Later in this section, to further examine temporal change explicitly across time, change in logged rates are further mapped as well. Ultimately, this initial stage will result in six maps, one for each of the three type-specific crime rates across the two time periods (1990 and 2000). We relegate these results to the chapter appendix but discuss them here in the narrative text.

In the appendix, the results for the spatial distribution of these logged rates are illustrated in figures A.1 – A.6. Figure A.1 illustrates the logged total crime rate per 100,000 individuals in 1990. From figure A.1, one can begin to identify global patterns concerning the distribution of the total crime rate across the U.S in 1990. It is important to note that because of the scale of the maps (covering the entire U.S.), places do not show up as distinctly and this maps primary purpose is to simply give a general understanding of how the total crime rate is distributed across the entire country (Monmonier 1996). The East and West Coasts, especially in the southern regions of each, had higher total rates of crime in 1990 when compared to other areas of the U.S. Localities in the upper Midwest, near Chicago and Detroit, also had a higher total crime rate in 1990.

Similar results can be seen in figures A.2 and A.3, respectively representing the logged property crime rate and violent crime rate per 100,000 in 1990, respectively. It is important to note that, in general, violent crimes occur at a lower rate than property crime and the scales displayed in a psudeo-natural brakes method with standardized values are slightly different based on that 'social fact'. However, a few discrepancies to this pattern can be observed. For instance, in southern California, South Carolina, and Florida, the violent crime rate in 1990 was noticeably higher than the property crime rate in the same year.

This is the first evidence that type-specific crime rates tend to behave differently in association with there geographic distribution.

The same approach was taken in mapping the type-specific raw crime rates per 100,000 in 2000. Figure A.4 displays the results for the total crime rate in 2000. The geographic pattern of the total crime rate in 2000 is not very different from the distribution of the total crime rate in 1990. However, spikes developed over the period in southern Nevada, Maryland, southern Arizona, and intensified in South Carolina and southern California. As with the identification of geographic differences in type-specific crime rates, this is the first evidence that criminal offending varies across temporal time periods within similar geographic localities. However, as pointed out above, the dynamics of this relationship are not random and tend to spatially situated in particular geographic contexts. This re-distribution of crime tended to focus on the intensification of crime in areas that had already had a moderate level of crime in 1990, while neglecting to encroach on the middle of the country where crime rates remained low, perhaps hinting at a contagious diffusion to nearby areas, which will become the focus of investigation in a subsequent chapter.

Figures A.5 and A.6 illustrate the logged property crime rate and violent crime rate per 100,000, respectively for the year 2000. From figure A.5, similar patterns associated with the re-distribution of the total crime rate in 2000 are at play, as similar areas emerge having higher rates of property crime than they did in 1990. Primary these areas include, once again, southern Nevada, southern Arizona, northwest New Mexico, and include intensifications in South Carolina and Maryland. Figure A.6 illustrates the logged violent crime rate per 100,000 in the year 2000 and these patterns show distinct areas of the country that have noticeably higher rates. These higher rates of violent crime in 2000 are almost exclusively centered in the states of Nevada, Florida, South Carolina, Maryland, Delaware, New Jersey, and portions of California, New Mexico, and Texas. In relation to the violent crime rate in 1990, these areas of high crime seem to have re-distributed away from some of the areas in the Midwest, like Illinois, following the overall and property crime rate to the southern U.S.

Due to the general visually-identified patterns associated with the raw rates presented in the first six figures of the Appendix and the previous notation of the instability of annual crime rates in localities with small populations or low occurrence, locally smoothed crime rates were also examined in order to more reliably identify potential patterns in the type-specific crime rates by year, across the study areas. Furthermore, insets from the north Georgia area, focused on the City of Atlanta, were used in insets to each map in order to give a clearer picture of the inter-relation of places and non-places associated with any further analyses. While the choice of this locale is arbitrary, it does give a consistent spatial reference with which to illustrate spatio-temporal patterns in the ecology of reported crime in the U.S.

Locally Smoothed Type-Specific Crime Rates

The rate used to create these smoothed patterns, as outlined in Chapter III's model specifications section, is the Local Empirical Bayes Smoother (Waller and Gotway 2004). This smoothed rate makes use of the identified neighborhood, or all regions that share a common border in order to compute a local neighborhood average for each of the localities. This method results in maps that are easier to visually interpret in terms of geographic distribution and variation across the study area. As with the logged crime rate maps in the Appendix, this spatially centered exploratory analysis yields six maps, one for each smoothed type-specific crime rate at both points in time.

Figure 9 illustrates the locally smoothed rate of the total crime in 1990. The figure is similar to the raw rate map of the total crime rate in 1990, but it does diminish the impact that a few of the spatial outliers made in the original raw rate map. This is one of the advantages of using a smoothed rate, in that it helps to control for unstable rates by introducing a local "neighborhood" average (Waller and Gotway 2004). For example, the high rates of crime in the states of New Mexico and Arizona have regressed towards a more moderate rate, which

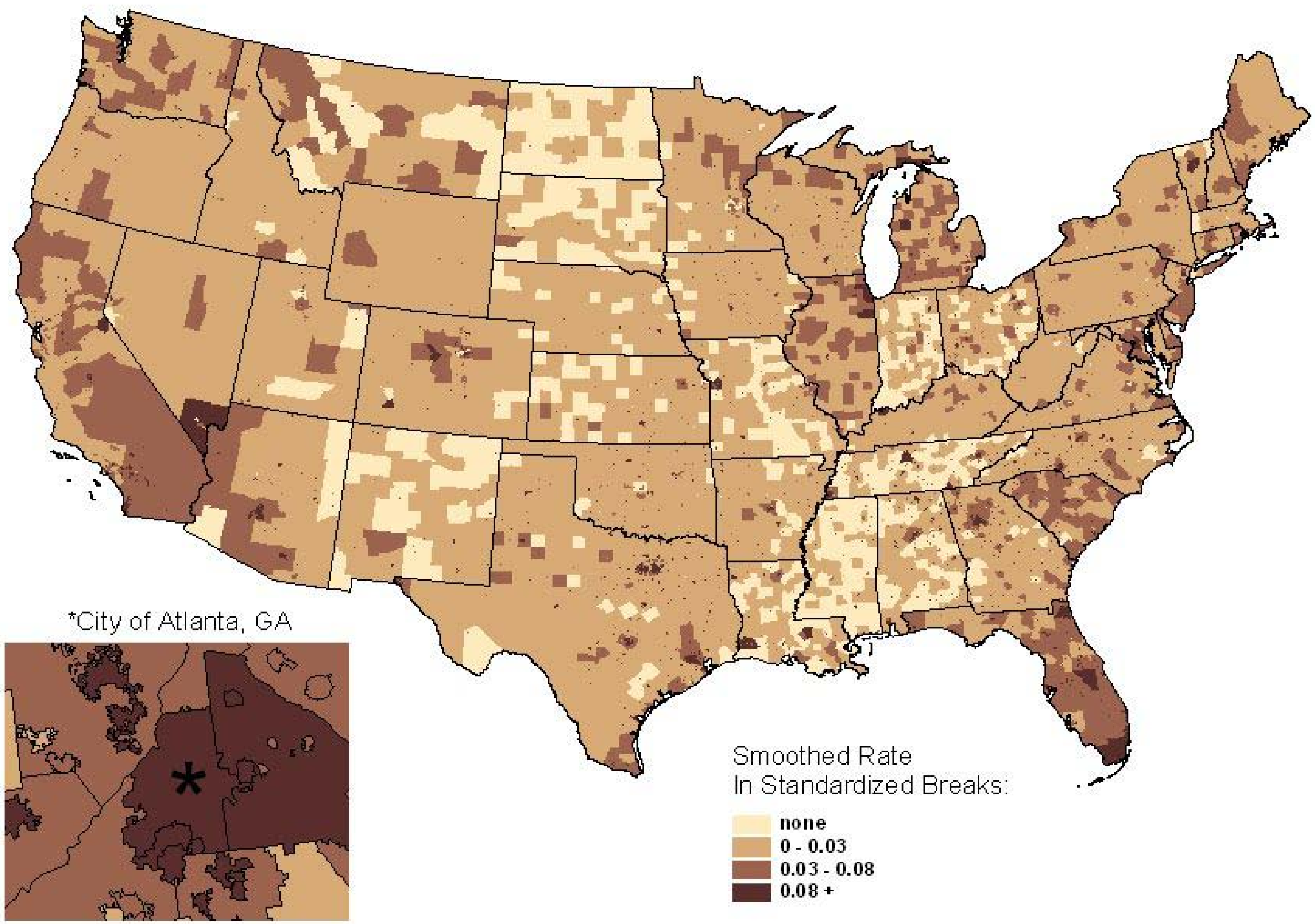


Figure 9. Local Empirical Bayes Smoothed Logged Total Crime Rate, 1990

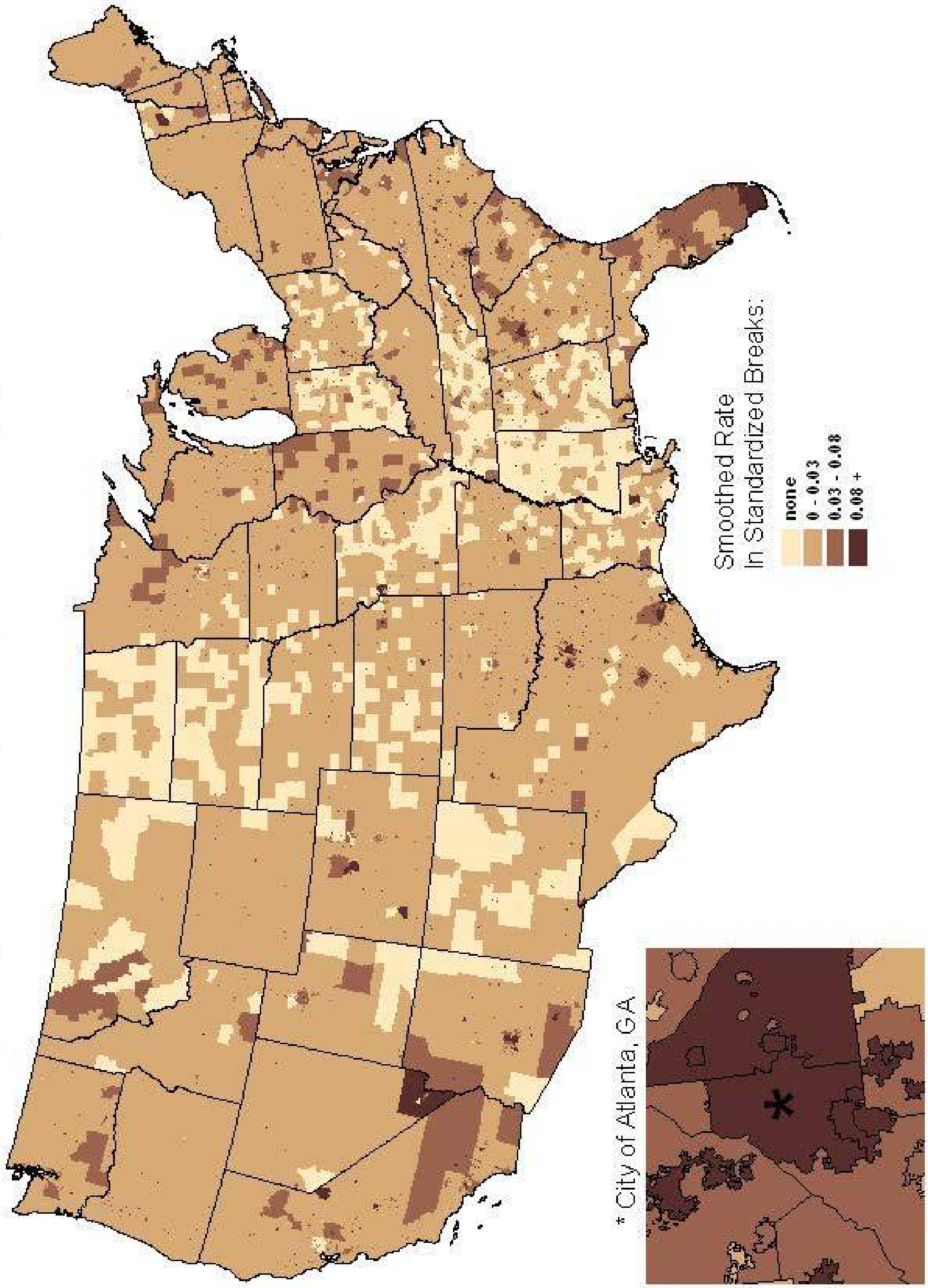
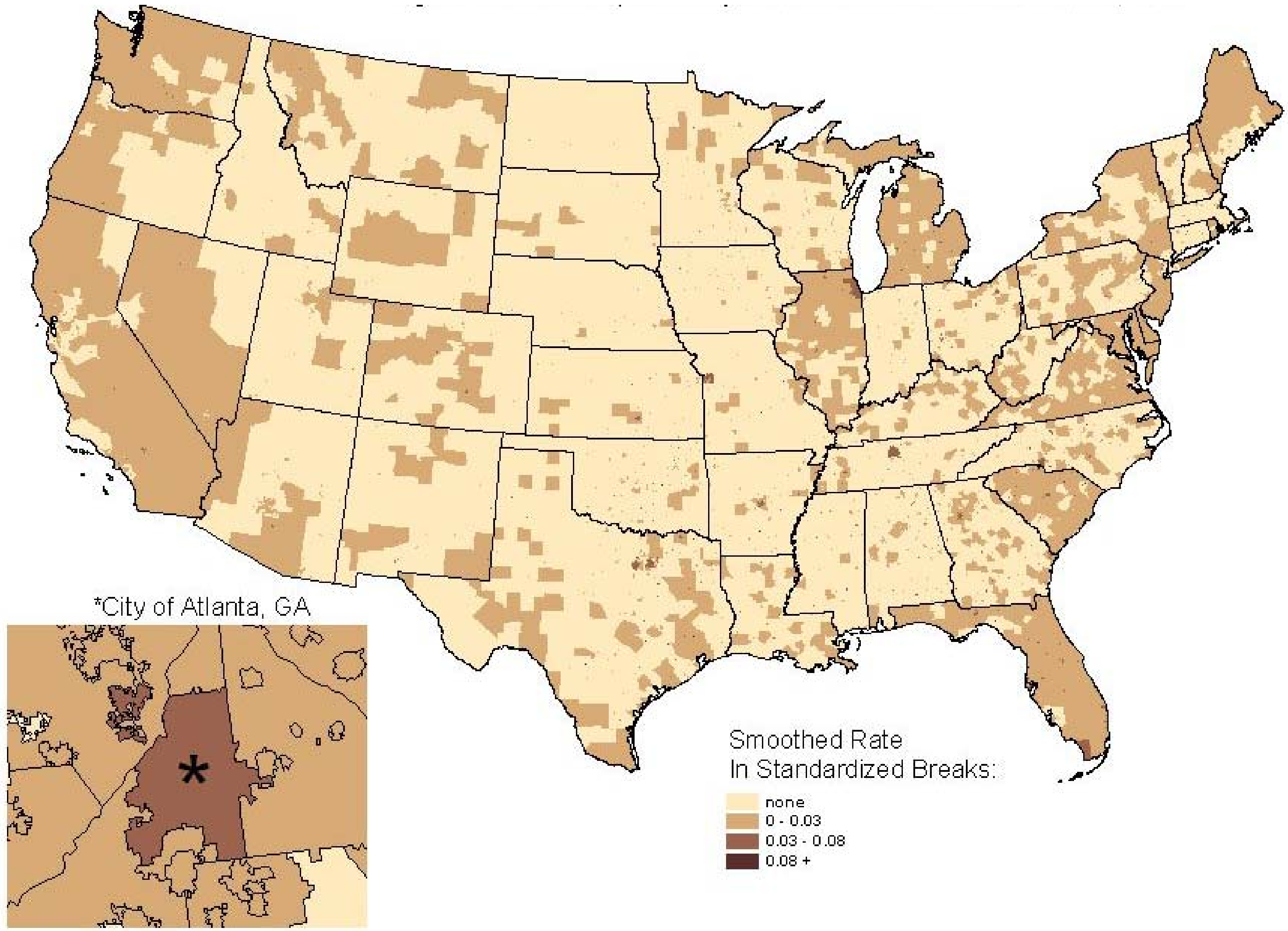


Figure 10. Local Empirical Bayes Smoothed Logged Property Crime Rate, 1990



is

Figure 11. Local Empirical Bayes Smoothed Logged Violent Crime Rate, 1990

more the norm in the region. Also, it has become evident that the high rates of crime tend to be centered on clusters of large places, such as Atlanta, Orlando, Baltimore, or Dallas. This lends support to the literature which states that crime acts in a distance-decay fashion in that the further from the city center, the less crime encountered, or at least, reported (Ackerman 1998).

In the inset of figure 9, results for the city of Atlanta are shown (as demarcated by the asterisk). From this inset, it shows that the city of Atlanta and DeKalb County, the large non-place territory directly to the East, as well as the Forrest Park area to the south and the Marietta area to the northwest, are all in the highest category, in terms of the total crime rate. Likewise, Henry County, directly to the southeast of Atlanta, has a relatively low rate and the most of the area to the West, primarily made up of Fulton, Cobb, and Douglas County, has a relatively moderate rate of crime.

Figures 10 and 11 represent the locally smoothed crime rates, respectively, for property and violent crimes in 1990. Figure 10 illustrates that property crime in 1990 tends to cluster in Florida, north Georgia, and South Carolina. Likewise, the violent crime in 1990 clusters even more intensely fashion in Florida and South Carolina, while also clustering in southern California, Maryland, Delaware, and New Jersey. When examining the insets of each, it is even more evident that the two type-specific rates behave differently across geographic space, as the spatial distribution of the property crime rate in Atlanta appears to be much more similar to the total crime rate than does the small-scale pattern of the violent crime rate. The most noticeable difference between the two being the much lower rate of violent crime offending, in comparisons to property crime offending.

The type-specific smoothed crime rates tend to be a little more accentuated in relation to the 2000 data. Figure 12 illustrates the locally smoothed total crime rate in 2000. The figure is noticeably different across several regions, especially in the upper South, where Tennessee is a potential area of clustering and is visually different from Kentucky to the north and Alabama and Mississippi to the south. This patterning is much different from the raw rate shown in figure VII4, where there is a much more random pattern associated with the region. Furthermore, the smoothed rates also seem to cluster on the east coast from Florida on north into the New Jersey/New York area. The latter is not unlike the raw rate, where similar visual clusters also existed along the East Coast.

Perhaps the most interesting finding here concerns the dramatic shift in the total rate of crime in the Atlanta area compared to ten years earlier. Since all of the maps contain the same scale, it is alright to compare across years. From the inset in figure 12, it is evident that the city of Atlanta had a lower rate of

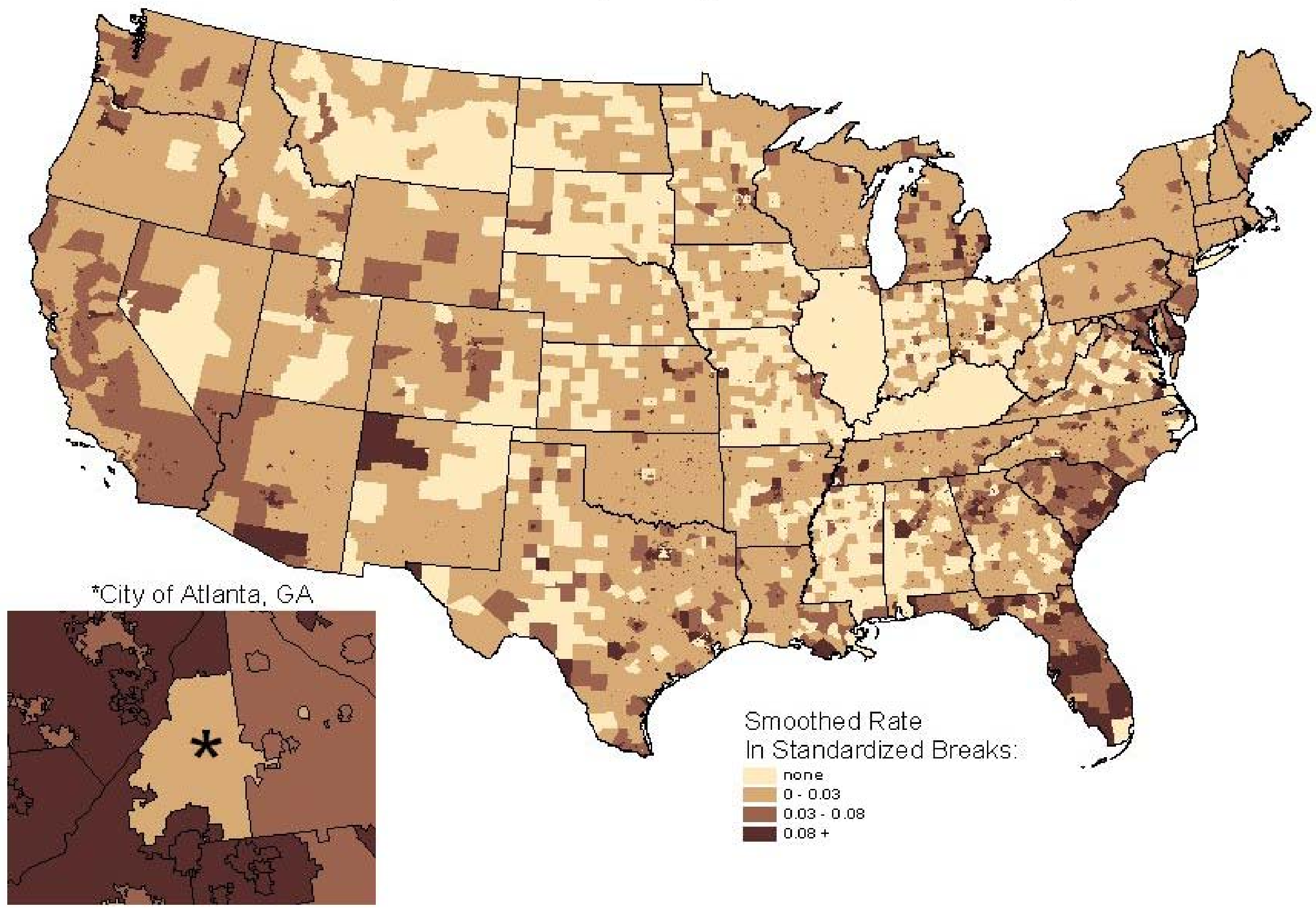


Figure 12. Local Empirical Bayes Smoothed Logged Total Crime Rate, 2000

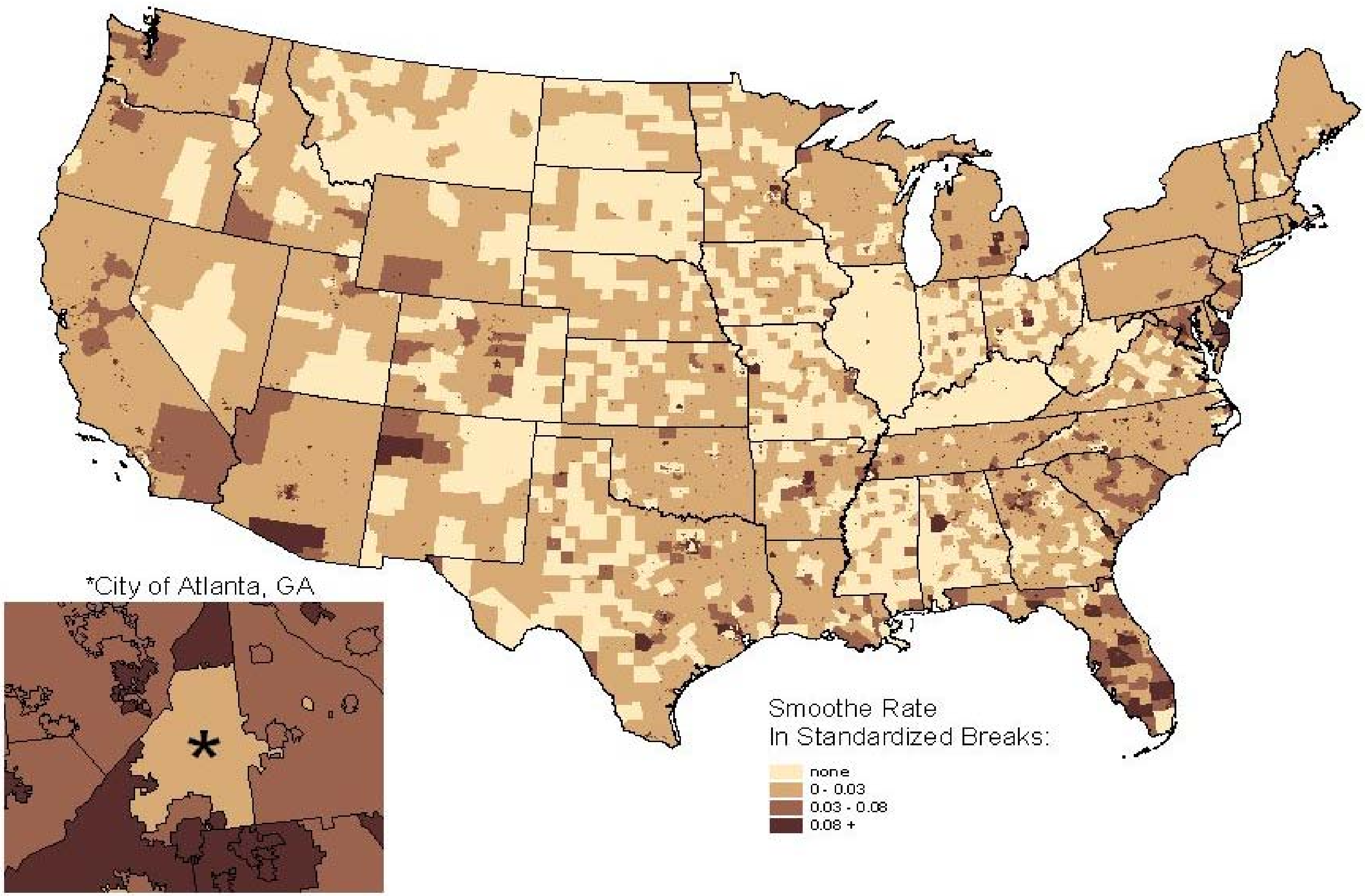


Figure 13. Local Empirical Bayes Smoothed Logged Property Crime Rate, 2000

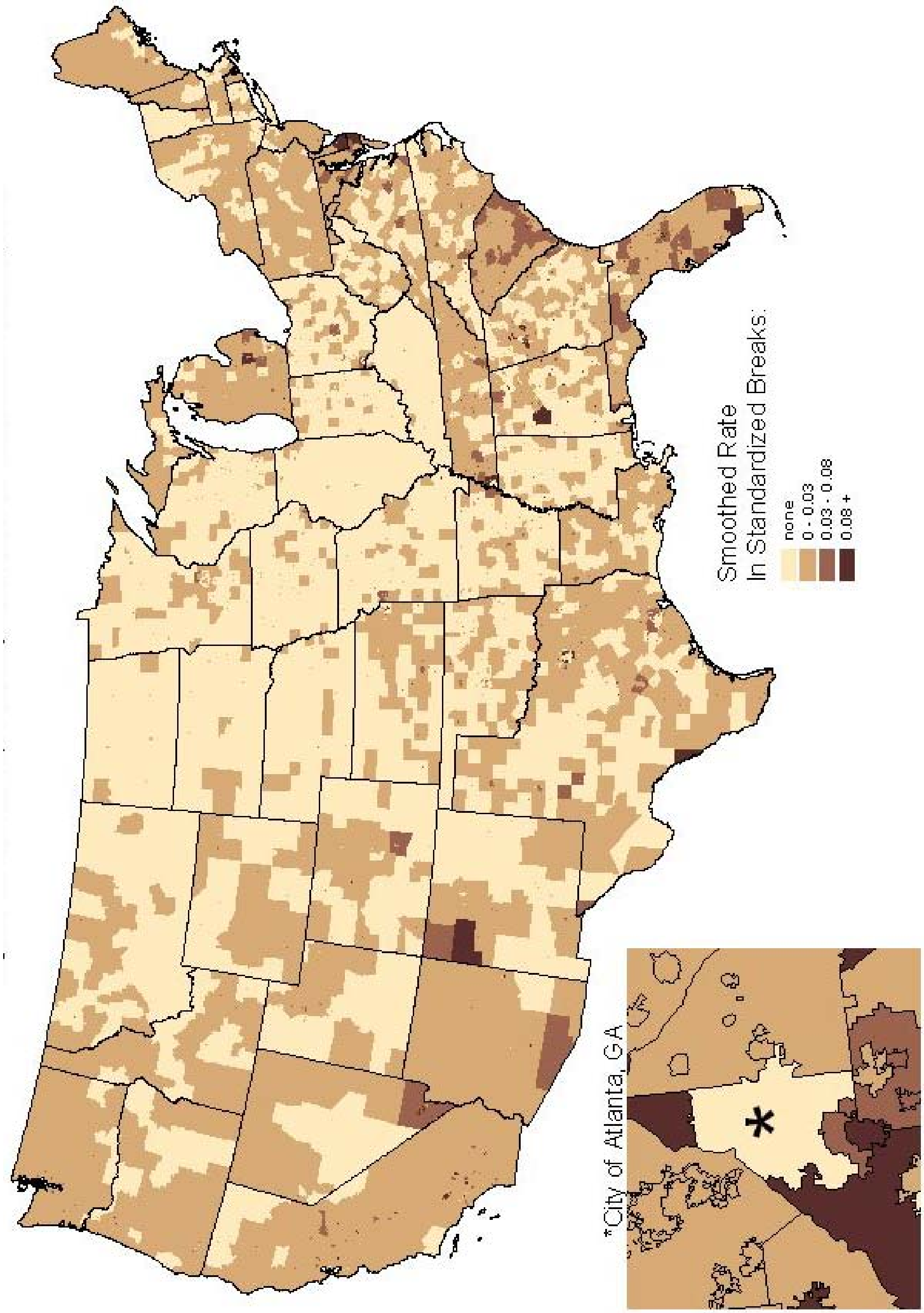


Figure 14. Local Empirical Bayes Smoothed Logged Violent Crime Rate, 2000

crime

crime than any of areas directly visible within the boundaries of this inset sub-region. Furthermore, when comparing this to the same inset in figure 9, total crime in 1990, it is evident that some process of spatial mobility seems to be at play. It appears as though there is evidence of displacement, in which the higher rate at time one spreads outwards, in a diffusion fashion of *relocation*, to contiguous areas (Paulsen and Robinson 2000). The simple identification of such a process lends creditability to the continued spatio-temporal analyses that have been outlined to be performed throughout the remainder of this dissertation.

Figure13 and 14 illustrate the locally smoothed property crime and violent crime rates, respectively. In figure 13 it is evident that similar patterns exist when compared to figure 12 above, the locally smoothed total crime rate for the same year. As before, there are distinct patterns across the Tennessee area, where high rates stretch into northern Georgia and on into South Carolina. Another interesting point in regards to figure 14 is that the high crime rate in Nevada (figure AVII6), based on the logged violent crime rate, disappears and regresses more towards the regional average. This is an important benefit of the EB smoother, to minimize the aberrant influence of large polygons like the counties in Nevada.

When examining figure 14, similar patterns are evident with the upper Midwest having a very low locally smoothed crime rate and high rates clustering in Tennessee, Florida, South Carolina, Maryland, Delaware, New Jersey, south Arizona, and southern California. Also important, the spatial shift in the total crime rate around Atlanta seems to be closely related to both property and violent crime, but especially the latter.

From the initial results of the raw rate maps, in the Appendix, and the locally smoothed rate maps, figures 9 - 14, it is evident that, upon visual inspection, spatial clustering seems apparent. In all cases, certain geographic areas had consistently higher or lower rates across both temporal periods. The locally smoothed rates helped to accentuate these patterns, especially in the 2000 type-specific crime rates. It is also evident that higher crime rates tend to cluster around larger metropolitan areas, as is the case around areas such as Atlanta, Dallas, Washington D.C., New York, Los Angeles, Chicago, Detroit, and so on.

Based on these spatially related patterns, it is appropriate to formally test for spatial dependence so as to have some assurance that what is seen does indeed represent high probability occurrences of spatial patterns.

Spatial Dependence in Criminal Offending

In order to test for spatial dependence, the global Moran's I test was implemented on each of the type-specific crime raw crime rates, using the earlier specified first order queen's neighborhood matrix (Anselin 1995; 1998). The results from the global Moran's I test will allow for the application of a formal test of significance in order to more assuredly identify non-random spatial patterns. The test statistic ranges from negative to positive, with zero being a perfectly random distribution and a significantly positive coefficient indicating a clustering patterns based on the value of interest, in this case each of the type-specific crime rates. Finally, if there are significant spatial clusters, the Local Indicator of Spatial Association (LISA) will be implemented in order to identify which areas of the country contain small 'neighborhoods' of spatially related crime rates (Anselin 1995 here).

Figure 15 is illustrates the results from the global Moran's I and the LISA tests for the total crime rate in 1990. It is evident from the Moran's I coefficient of 0.1302, significant at less than $p < .01$ based on the randomization significance test with 999 permutations. The positive coefficient indicates that there is positive spatial clusters of the total crime rate in 1990. This means that areas close together tend to be more alike than areas far apart. This confirms some of the visual patterns evident in the raw rate maps and the locally smoothed rate maps of the total crime rate in 1990.

Figure 15 also introduces the results of the LISA via the five category legend in the bottom left hand corner. The five categories consist of a non-significant category, a High-High category, a Low-Low category, a Low-High

Category, and a High-Low category. In each of the latter four categories the first value is related to the total crime rate of the i^{th} region and the second value is associated with the average neighbor's crime rate. Based on that definition, a High-High area is an area with a high crime rate surrounded by neighbor's that, on average, have a high crime rate. Likewise, a Low-Low area is an area with a low crime rate surrounded by neighbor's that, on average, have a low crime rate. Both of these indicate positive spatial clustering, in which areas close together are more alike that those far apart.

In contrast, areas that are in the High-Low category are areas with a high crime rate surrounded by neighbor's that, on average, have low crime rates and vice-versa in regards to being in the Low-High category. In each of these two cases there exists negative spatial association, meaning that areas close together tend to not be alike in terms of there crime rates. Based on the global Moran's I coefficient, which is positive, it is appropriate to posit that more significant areas will be in the High-High or Low-Low categories based on the fact that there exist positive spatial association, or spatial clustering.

The results from the LISA procedure in figure 15 illustrate a number of significant pockets of association between neighboring counties. Some of the areas that are significantly in the High-High categories are located in the central and southern Florida, Southern California, and southern Arizona. Likewise,

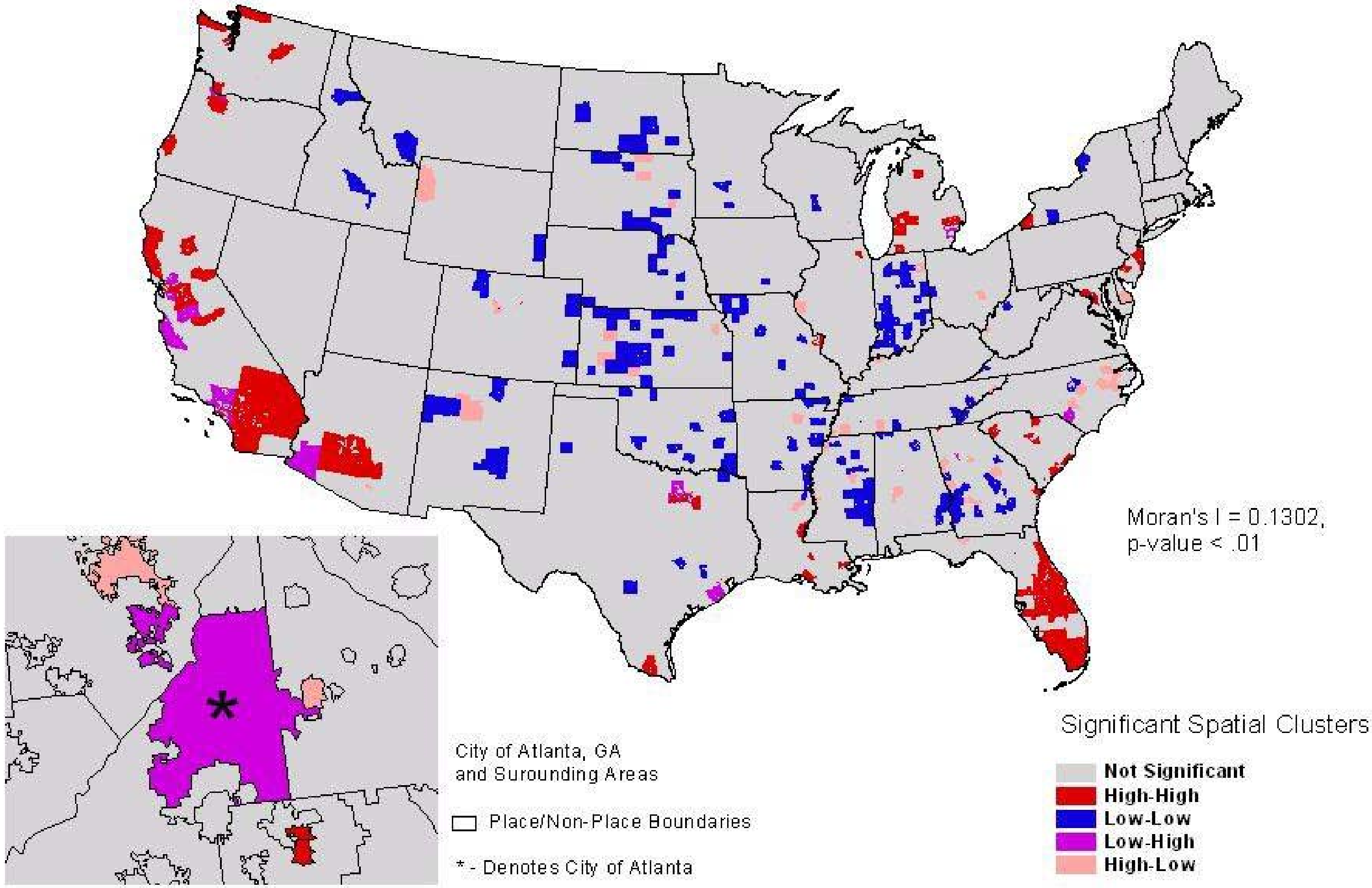


Figure 15. Significant Spatial Clusters of Total Crime Rate, 1990

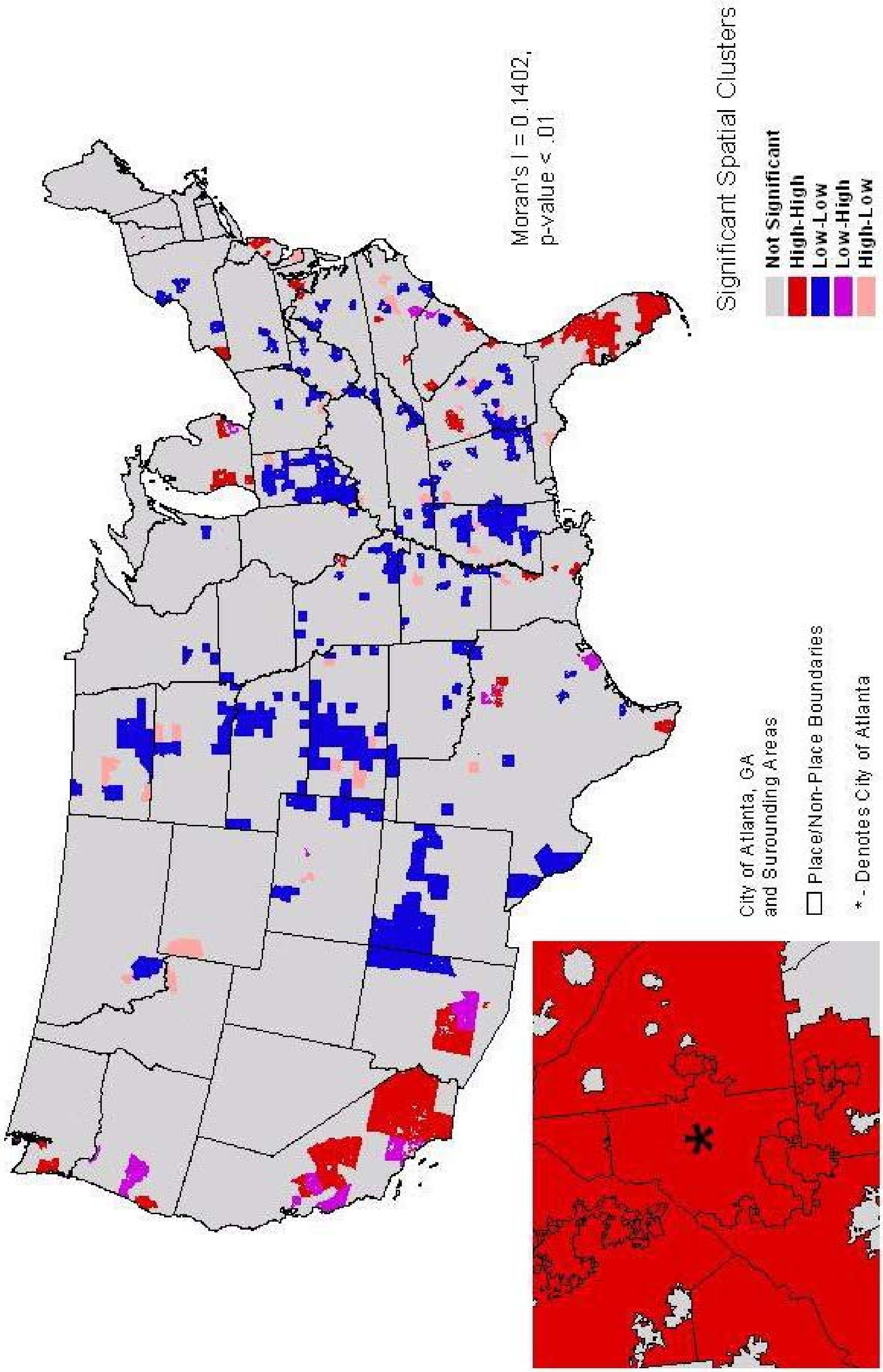


Figure 16. Significant Spatial Clusters of Property Crime Rate, 1990

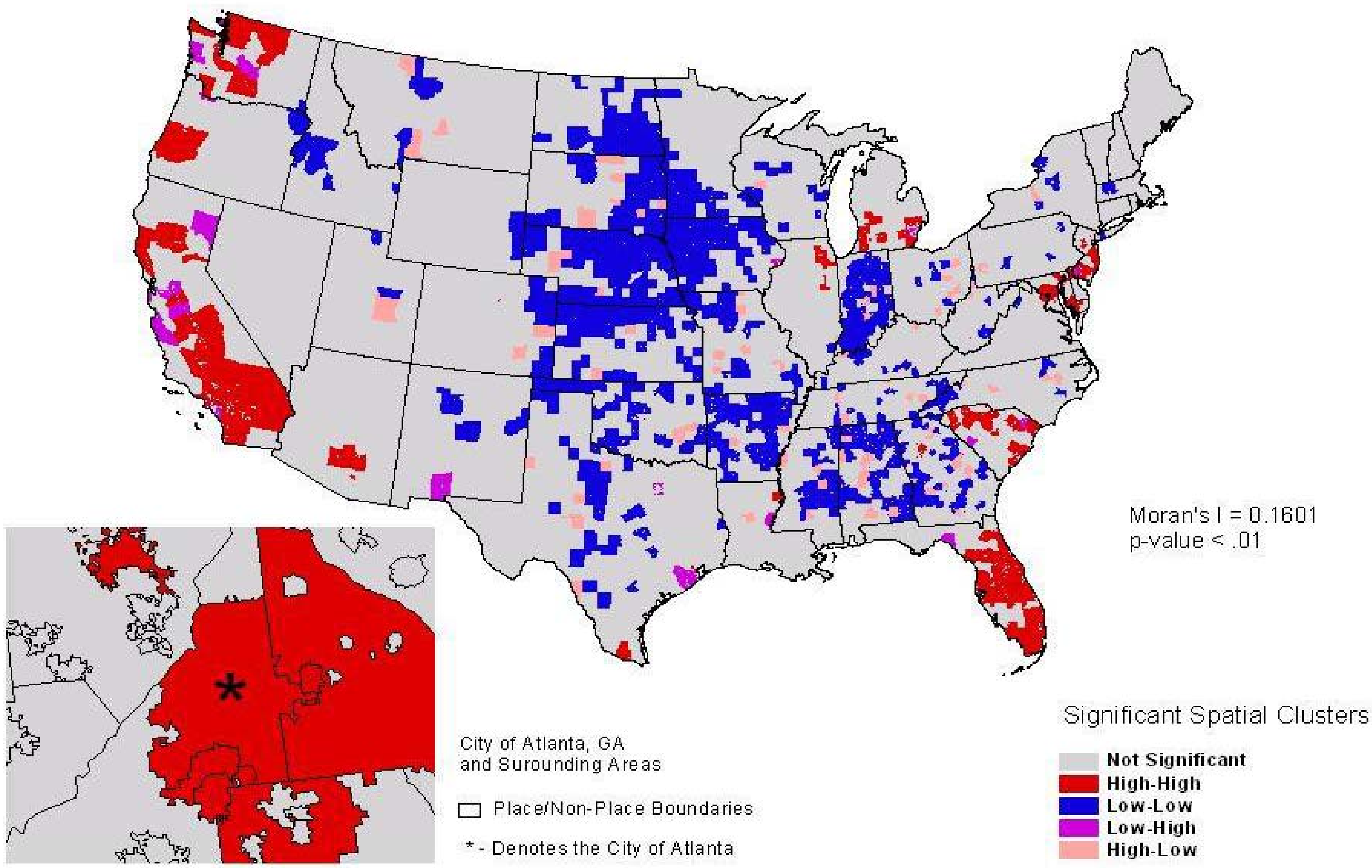


Figure 17. Significant Spatial Clusters of Violent Crime Rate, 1990

there is positive spatial clustering of low total crime rates in 1990, via the Low-Low category, throughout the Midwest, especially in Nebraska, Indiana, and Kansas. There are also a number of areas in the Low-High and High-Low categories, as well as a number of significant areas not identifiable due to resolution (as places are often too small to appear in a full-scale continental U.S. map).

Furthermore, in the inset, the dynamics associated with the place-level geographies in terms of their significant spatial clustering are fairly clear. First, the city of Atlanta is low in terms of the total crime rate and is significantly situated around areas that are high in reported criminal offending. To the south of the city there is another group of places, including Lake City and Morrow, in the Forrest Park area that make up a significant high cluster and to the east and north places of high crime significantly situated in neighborhoods of lower criminal offending rates. Relative to the thesis of this study, there are no non-place territories that are significantly part of a significant cluster of crime or the lack of crime.

In figure 16, the property crime rates in 1990 are examined for potential spatial clustering. It is evident that spatial clustering does exist, as the Global Moran's I coefficient of 0.1402 indicates significant positive spatial clustering. Similar patterns exist in regards to the locations of the significant clusters of high and low property crime rates. Primarily, Florida and California continue to have large clusters, while Indiana, Kansas, Nebraska, as well as New Mexico and North Dakota all have significant high clusters of low property crime rates. Furthermore, in the inset, the entire area surrounding Atlanta, especially the non-places, are all situated in a high cluster of criminal offending, in regards to property crime.

Spatial clustering was next tested on the violent crime rate in 1990, as presented in figure 17. The results show that there is significant spatial clustering based on the fact that the Moran's I coefficient is positive and equal to 0.1601. As with the previous two tests the coefficient is significant at less than the .01 level using the randomization significance test at 999 permutations. The positive spatial association is based on the large cluster of low violent crime rates across the upper Midwest and on into the South and along the black-belt region across Arkansas, Mississippi, Alabama, and Georgia. From the pockets of areas categorized as High-Low, there are a number of place-level geographies, in which areas of high violent crime rates are surrounded by neighbor's that, on average, have low violent crime rates. Also, there are significant spatial clusters of high violent crime rates across Florida, South Carolina, New Jersey, Maryland, California, and Western Washington state, noticeable at the non-place level due to resolution meaning that the neighboring non-places and internal places are probably also high in offending rates.

Figure 18 illustrates the test of spatial dependence on the total crime rate in 2000. From the Moran's I coefficient it is evident that there exist positive spatial clustering. From the spatial distribution, it seems that the clusters are relatively similar to the LISA results of the total crime rate in 1990. There does, however, exist some deviations, for example, the High-High cluster in New Jersey has shifted to the west into Maryland. Also, the High-High clusters in South Carolina and Arizona have spread, while the clusters in Florida and California have shrunk or been displaced. Furthermore, the Low-Low clusters in Kansas seem to have shifted towards the west into Colorado.

Figures 19 and 20 illustrate the tests of spatial dependence on the property crime rate and the violent crime rate in 2000, respectively. In relation to figure 19, there exists positive spatial clustering based on the Moran's I coefficient of 0.1606. The significant spatial clusters of property crime are again relatively similar with the development of High-High clusters in the Northwest and in central Florida. Likewise, there were significant Low-Low clusters of property crime that developed in New Mexico, Idaho, and West Virginia over the ten year period.

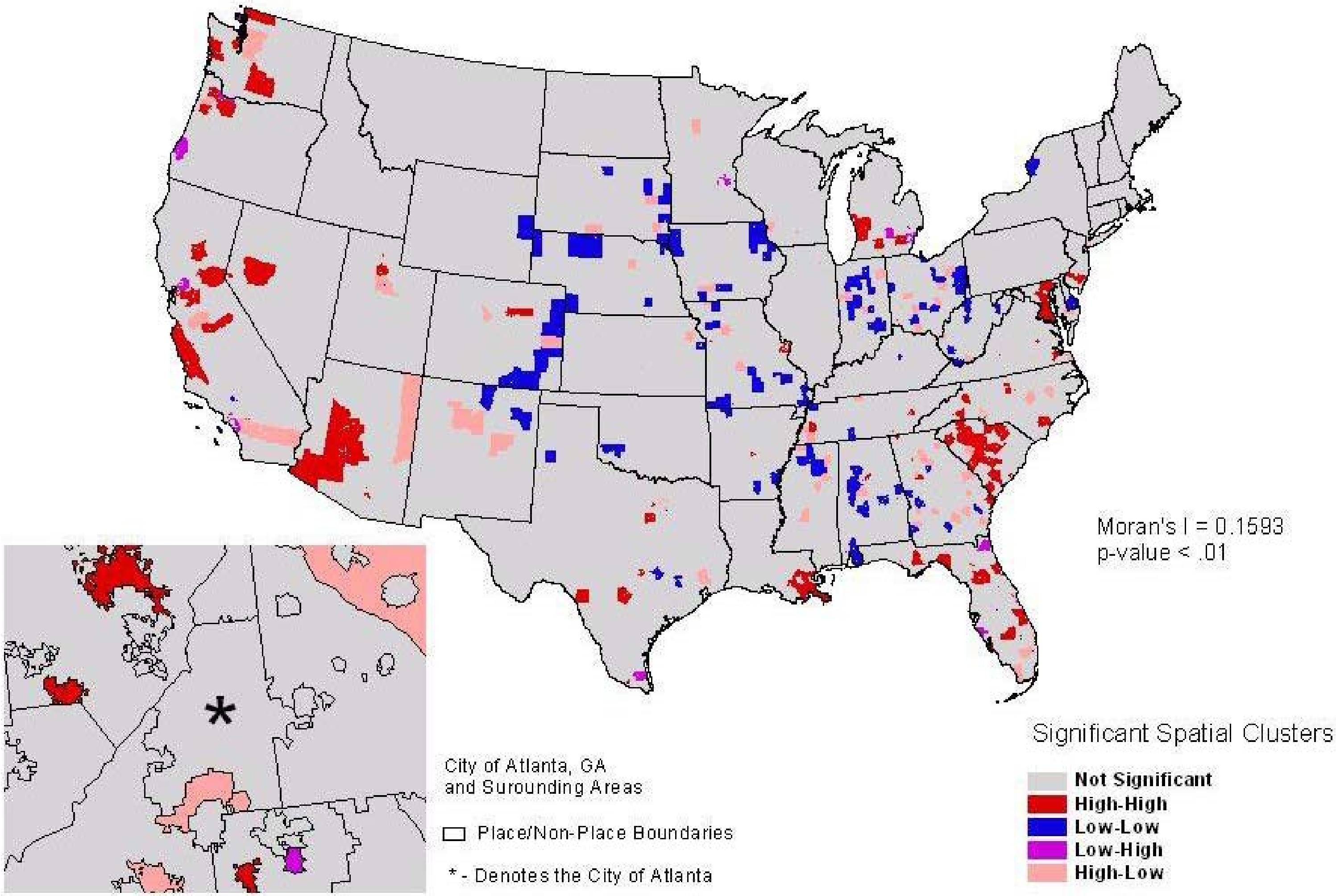


Figure 18. Significant Spatial Clusters of Total Crime Rate, 2000

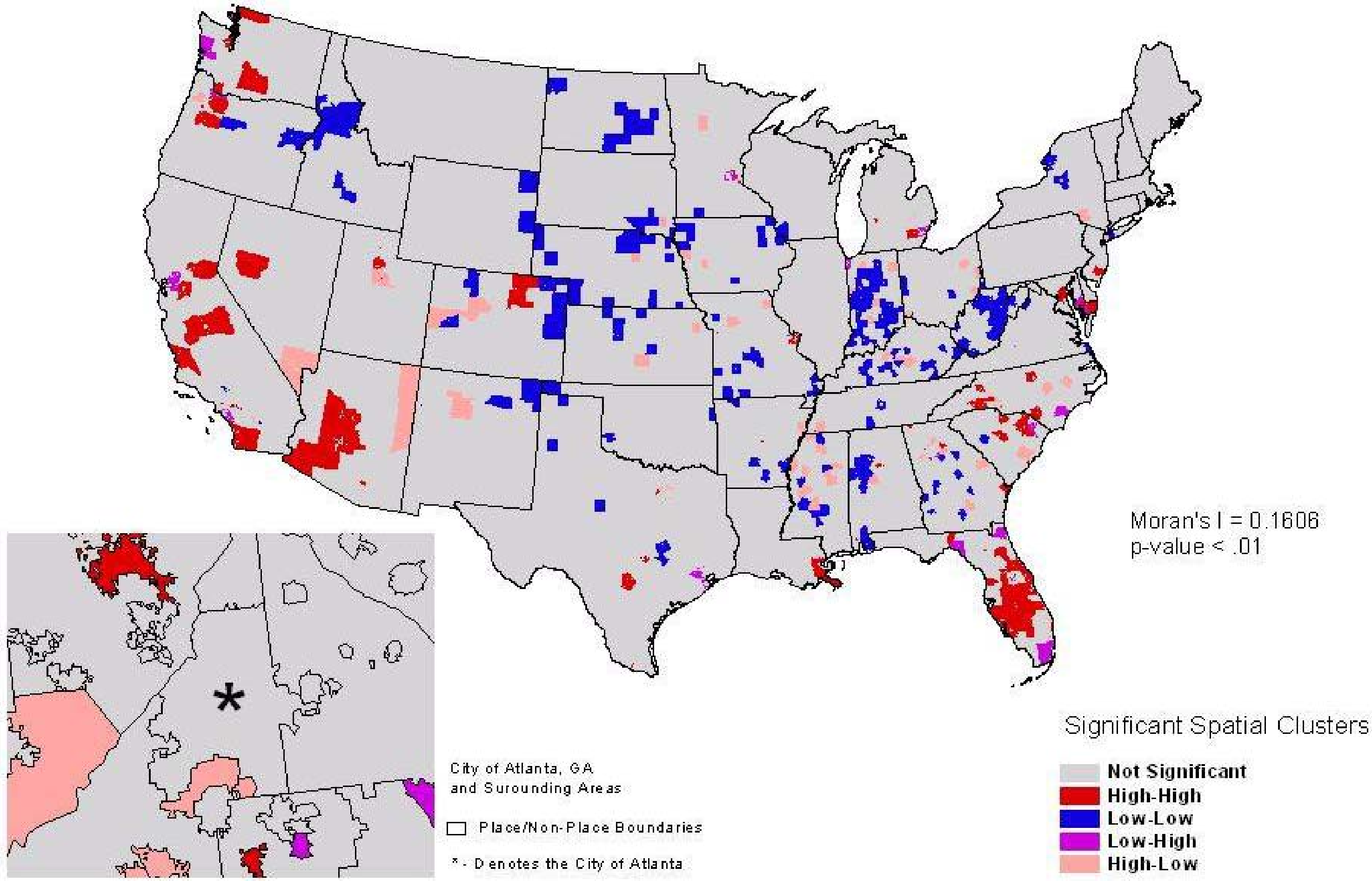


Figure 19. Significant Spatial Clusters of Property Crime Rate, 2000

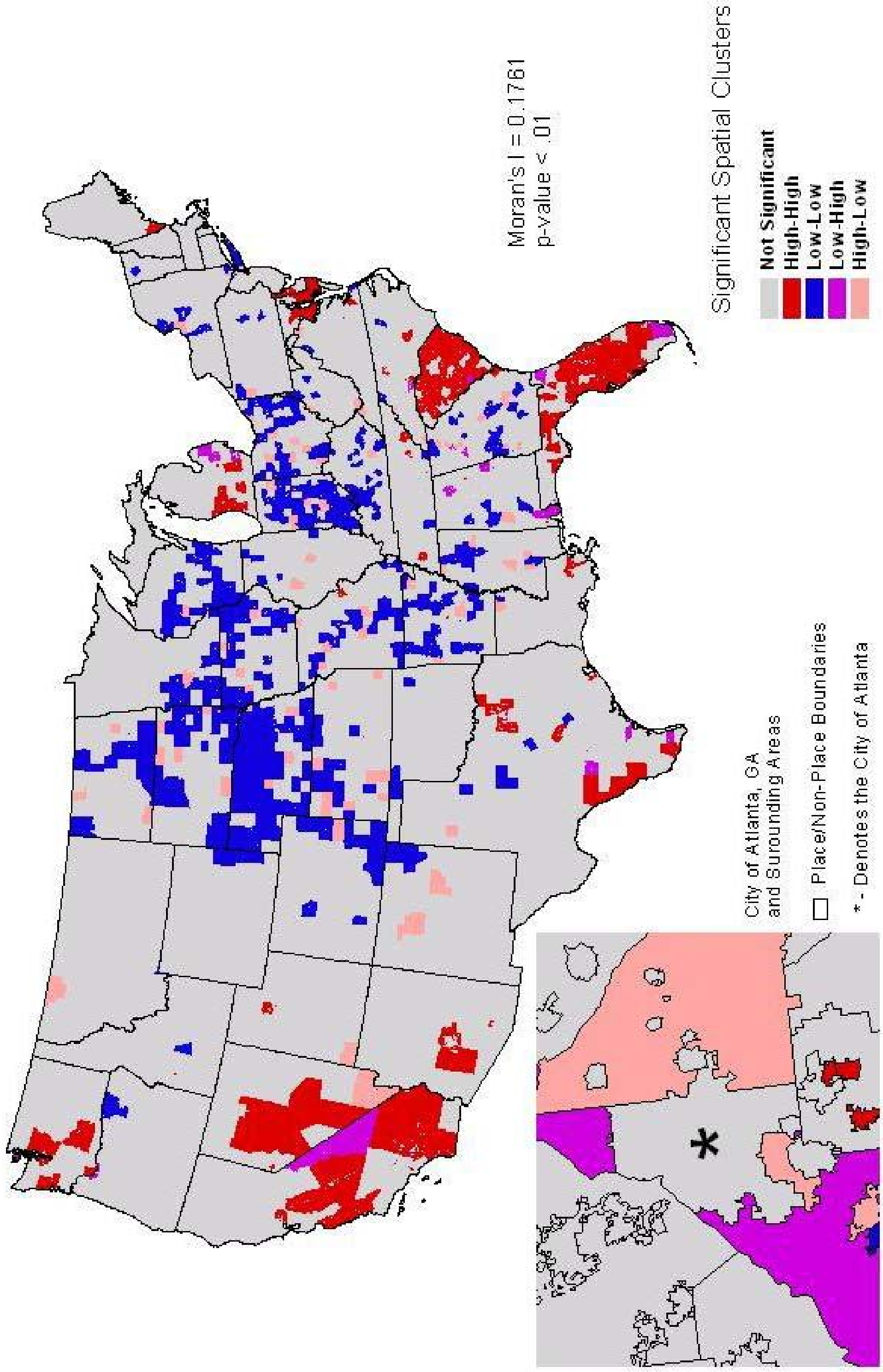


Figure 20. Significant Spatial Clusters of Violent Crime Rate, 2000

In

relation to violent crime in 2000, shown in figure 20, there is significant positive spatial association based on the Moran's I coefficient of 0.1761. The High-High clusters of violent crime have spread in South Carolina and north Florida, while the significant Low-Low clusters seem to have shrunk or been displaced across the Midwest and the deep South. Again, all spatial dependence tests were significant at the $p < .01$ level using the randomization significance test with 999 permutations.

From the spatial description of the type-specific crime rates, a number of important questions have been addressed concerning the main thesis of this study that reported crime has important spatial components at the sub-county level. First, it is evident that there are definite spatial patterns that were both visually identified and statistically confirmed through formal tests of spatial dependence. It is also rather clear that the three crime rate measures act differently across geographic space and temporal points in time. Based on these findings, it is important to take this spatial dependence into account when subsequent estimating regression models through the implementation of appropriate diagnostics and autoregressive spatially regression models (Anselin 1995; Waller and Gotway 2004)

Mean Differences in Type-Specific Crime Rates

Based on the above findings, it is important to continue to examine the dependent variables of interest across key geographically-related factors. This is undertaken in the last phase of this chapter, in which mean differences in crime measures will be examined using a repeated measures one-way ANOVA approach (Tabachnik and Fidel 2000)[8]. Ancillary analyses examined the individual effects of these classification variables, which are reported in tabular and graphical form in the Appendix [9]. These differences will be examined across place-level geography (place or non-place territory), metropolitan status, U.S. Census Region, and time period. Moreover, the magnitude of variation in the type-specific crime rate across the geographic units of interest will be examined using the partial eta-square statistic (Ott and Longnecker 2000)

Table 6 introduces a twenty-four category classification system across all possible combinations of place-level, metropolitan status, and U.S. region. By breaking down the type-specific crime rates across this multi-level classification system, it will allow for a more in depth look at the spatial heterogeneity that may exist in reported crime. The table is organized so that each row represents one of the twenty four categories, delineated by region, metropolitan status, and place-level in that order. Next, the second column represents the percentage of

Table 6. Type-Specific Logged Crime Rates by Spatial Categorization 1990 – 2000

Spatial Categorization	Percent of Cases	Type Specific Crime Rate (LN)*					
		Total Crime		Property Crime		Violent Crime	
		1990	2000	1990	2000	1990	2000
Northeast							
Metropolitan							
Place	8.6	8.02	7.76	7.79	7.44	6.21	6.22
Non-Place	1.5	7.72	7.55	7.50	7.21	6.06	6.36
Adjacent							
Place	1.8	7.80	7.62	7.58	7.37	6.07	6.03
Non-Place	0.9	7.69	7.58	7.44	7.14	6.14	6.45
Non-Adjacent							
Place	0.2	7.61	7.71	7.33	7.30	5.80	6.30
Non-Place	0.2	7.80	7.18	7.58	7.15	6.09	6.31
Midwest							
Metropolitan							
Place	8.1	8.46	8.36	8.24	8.08	6.65	6.81
Non-Place	2.6	7.31	6.95	7.07	6.88	5.67	5.97
Adjacent							
Place	4.1	8.18	8.16	7.97	7.89	6.42	6.62
Non-Place	4.3	7.10	6.71	6.91	6.60	5.34	5.56
Non-Adjacent							
Place	3.5	8.32	8.31	8.10	7.97	6.72	6.99
Non-Place	5.5	6.96	6.99	6.79	6.73	5.17	5.68
West							
Metropolitan							
Place	6.8	8.69	8.79	8.45	8.52	7.08	7.26
Non-Place	1.1	7.78	8.03	7.53	7.67	6.28	6.95
Adjacent							
Place	3.1	8.51	8.40	8.25	8.10	6.90	6.96
Non-Place	2.1	7.58	7.55	7.32	7.24	6.00	6.48
Non-Adjacent							
Place	1.5	8.58	8.39	8.35	8.11	6.96	7.07
Non-Place	1.7	7.41	7.31	7.18	7.00	5.79	6.21
South							
Metropolitan							
Place	12.4	8.50	8.62	8.28	8.32	6.73	7.22
Non-Place	4.8	7.73	8.02	7.54	7.63	6.10	6.97
Adjacent							
Place	9.1	8.09	8.32	7.84	7.94	6.54	7.02
Non-Place	7.2	7.37	7.39	7.14	7.02	5.60	6.29
Non-Adjacent							
Place	4.1	8.01	8.21	7.78	7.88	6.45	6.94
Non-Place	4.8	7.11	7.13	6.85	6.75	5.41	6.00
Eta-Square		0.165	0.168	0.143	0.179	0.189	0.126

* Mean differences across all spatial categories are significantly different at less than the 0.001 level.

Table 7. Main and Interaction Effects of the Logged Type-Specific Crime Rates By Selected Classifier Variables

Effect Classifiers	Partial Model Summary		
Total Crime Rate	**Type III Sum of Squares**	**F-Statistic**	**η_p^2**
Place-Level	405.15	313.850 ***	0.036
Metropolitan Status	80.22	31.073 ***	0.007
U.S. Census Region	143.45	37.041 ***	0.013
Place-Level*Metro	1.80	0.698	0.000
Place-Level*Region	103.09	26.618 ***	0.009
Place-Level*Metro*Region	56.89	3.672 ***	0.005
Intercept	150762.77	116787.440 ***	0.932
Error	10918.57	--	--
Property Crime Rate	**Type III Sum of Squares**	**F-Statistic**	**η_p^2**
Place-Level	387.91	315.867 ***	0.036
Metropolitan Status	85.83	34.946 ***	0.008
U.S. Census Region	100.56	27.295 ***	0.010
Place-Level*Metro	0.59	0.240	0.000
Place-Level*Region	79.10	21.469 ***	0.008
Place-Level*Metro*Region	54.70	3.711 ***	0.005
Intercept	140795.79	114648.200 ***	0.931
Error	10387.00	--	--
Violent Crime Rate	**Type III Sum of Squares**	**F-Statistic**	**η_p^2**
Place-Level	244.05	153.572 ***	0.018
Metropolitan Status	225.85	47.374 ***	0.005
U.S. Census Region	72.21	22.718 ***	0.017
Place-Level*Metro	10.54	3.315 *	0.001
Place-Level*Region	104.14	21.844 ***	0.008
Place-Level*Metro*Region	57.48	3.014 ***	0.004
Intercept	99422.32	62563.432 ***	0.881
Error	13440.98	--	--

η_p^2 - Partial Eta-Square = the proportion of the effect+error variance accounted for by the effect

*** p-value < 0.001

* p-value < 0.05

the total number of areas that fall into that category. Finally, a series of six columns reports the mean logged rate of crime by type of rate and year.

When all combinations of these three classifiers are examined via a repeated measures one-way analysis of variance the effects of the classifiers on the type-specific crime rate can be teased out for interpretation (Tabachnik and Fidel 2000). This procedure allows for the examination of estimated marginal means of between group classifiers given multiple levels of data (Norusis 2006; Tabachnik and Fidel 2000). In this case the multiple levels are the two points in time, meaning that the estimated marginal means take into account the difference in the between group classifiers given the variation in the levels (temporal period). The results of such an analysis are presented in table 7 organized by type-specific crime rate. Within the table a partial model summary is given, which includes the type III (3) sums of squares (used for computing the magnitude of the effect), and F-statistic with an associated significance value, and a partial eta-square (used to measure the magnitude of the effect in relation to the effect of the given error) (Tabachnik and Fidel 2000).

Of major importance here is the fact that the variation explained in the type-specific crime rate by the place-level classification has the largest meaningful effect. The fully-specified multi-level classification, represented by the three-way interaction, is weaker than all of the individual classifications and the place-level/region two-way classification, based on the eta-square statistic. This finding gives substantial evidence to the proposition stated above, that while criminal offending can be examined via large groups mean differences, such as those in the Appendix, there still exists a great deal of unexplained spatial variation. However, even more encouraging is the point that the newly introduce place-level geography has easily the strongest effect across all three type-specific crime models.

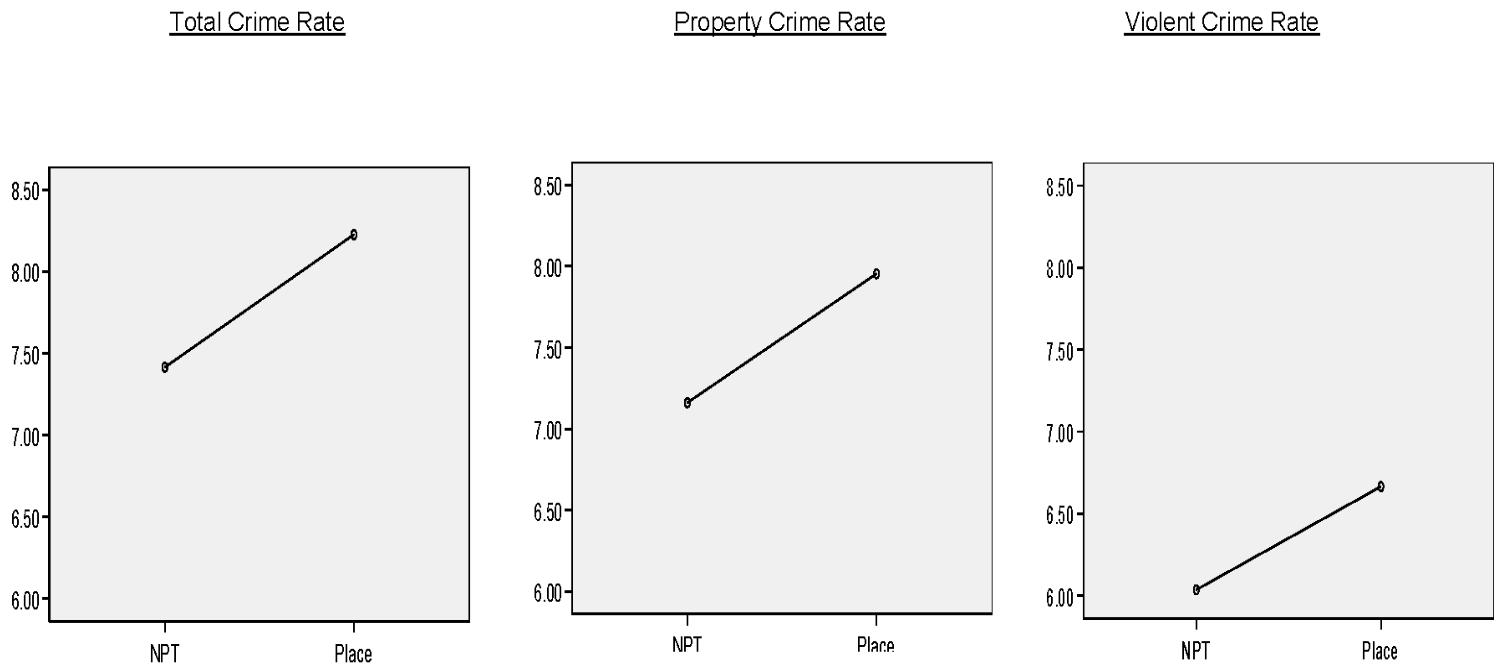
Based on that point, it is important to understand where some of the variation exists in order to identify potential patterns, drilling down below traditional classification variables. For example, the areas identified as places in the Northeast and are Non-Adjacent Non-Metropolitan counties are lower in type-specific crime rates for all three categories in 1990 and in violent crime in 2000 than are non-places within the same geography niche. This would not be expected based on the findings of the large mean groups above where places had a significantly higher mean level of type specific crimes than did non-places.

The next set of figures graphically illustrates the unique relationship of each type-specific crime rate broken down by place-level, region, and metropolitan status. It is important to explain the setup of the figures before further explaining them. Each of the figures presents mean-plots by place-level broken down into three crime type-specific lattices. These mean-plots are presented in figures 21 – 27. The mean-plots were produced by using the same repeated measures procedure in SPSS explained above (Noursis 2006).

In figure 21 – 24, the mean-plots of the type-specific crimes are examined across each of the four classifications. Figure 21 represents the mean-plot of the estimated marginal means by place-level. From the figure it is evident that crime is higher in places than non-places and that violent crime tends to occur, on average, much less than do the other types. This is not surprising given the above literature review that outlines the fact that places have a higher rate of crime than do non-places.

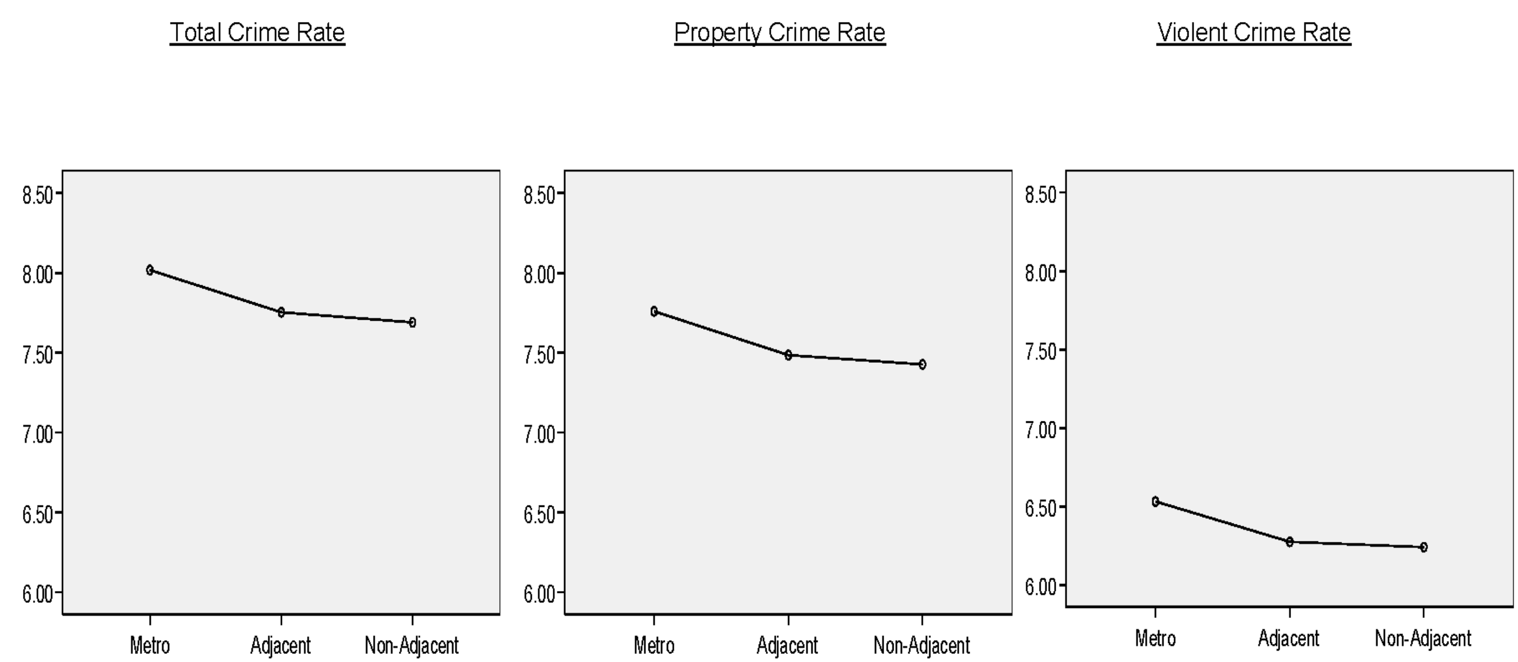
In figure 22 the mean-plot of the estimated marginal mean crime rate by metropolitan status is given. From the figure it is evident that metropolitan areas have a noticeable higher crime rate than do non-metropolitan areas. Among the two non-metropolitan classifiers, it seems that localities in non-adjacent counties have a slightly lower rate than those in adjacent counties. Violent crime, again is committed at a much lower rate than the other two type-specific crimes. This, like the previous results, is not surprising as urban areas are documented as having a consistently higher crime rate than rural areas.

Figure 23 presents the results of the mean-plot for the difference in criminal offending by U.S. census region. It looks as if there is little to no difference between the Northeast and the Midwest, while the West and the South



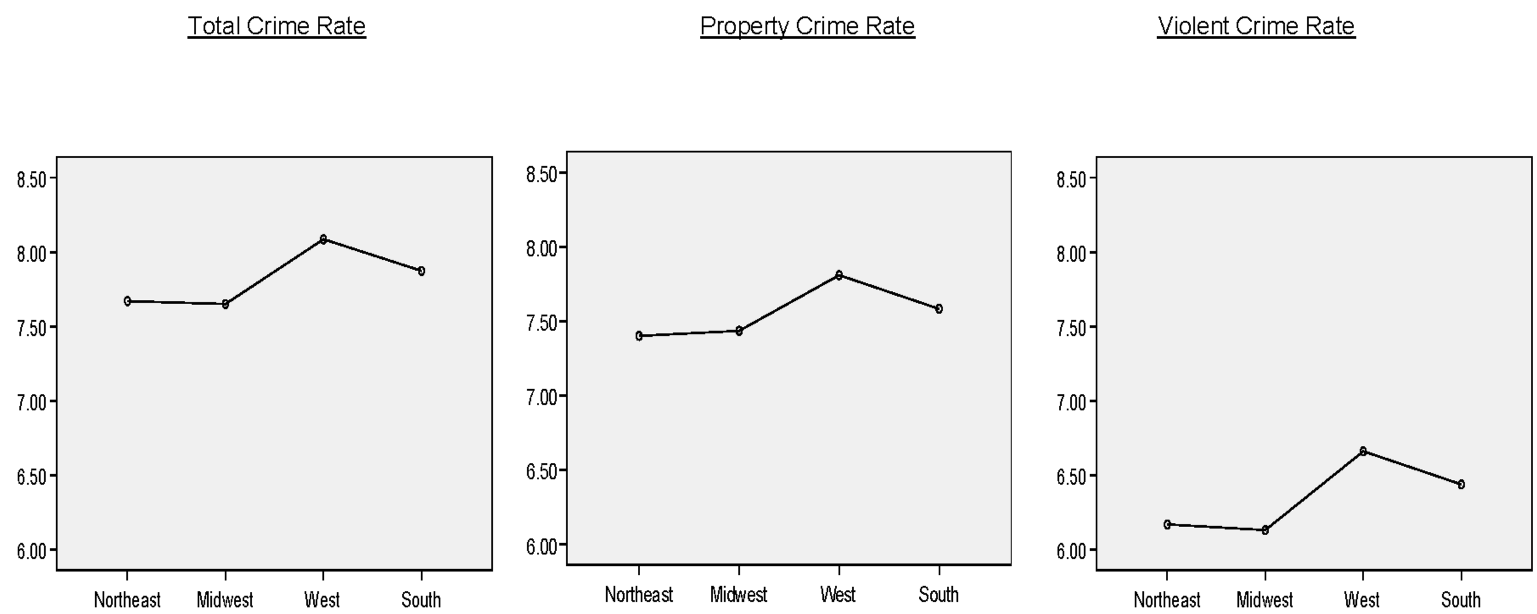
*NPT = Non-Place Territory; PLC = Place

Figure 21. Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Place-Level Using a Repeated Measures ANOVA Approach, 1990 – 2000



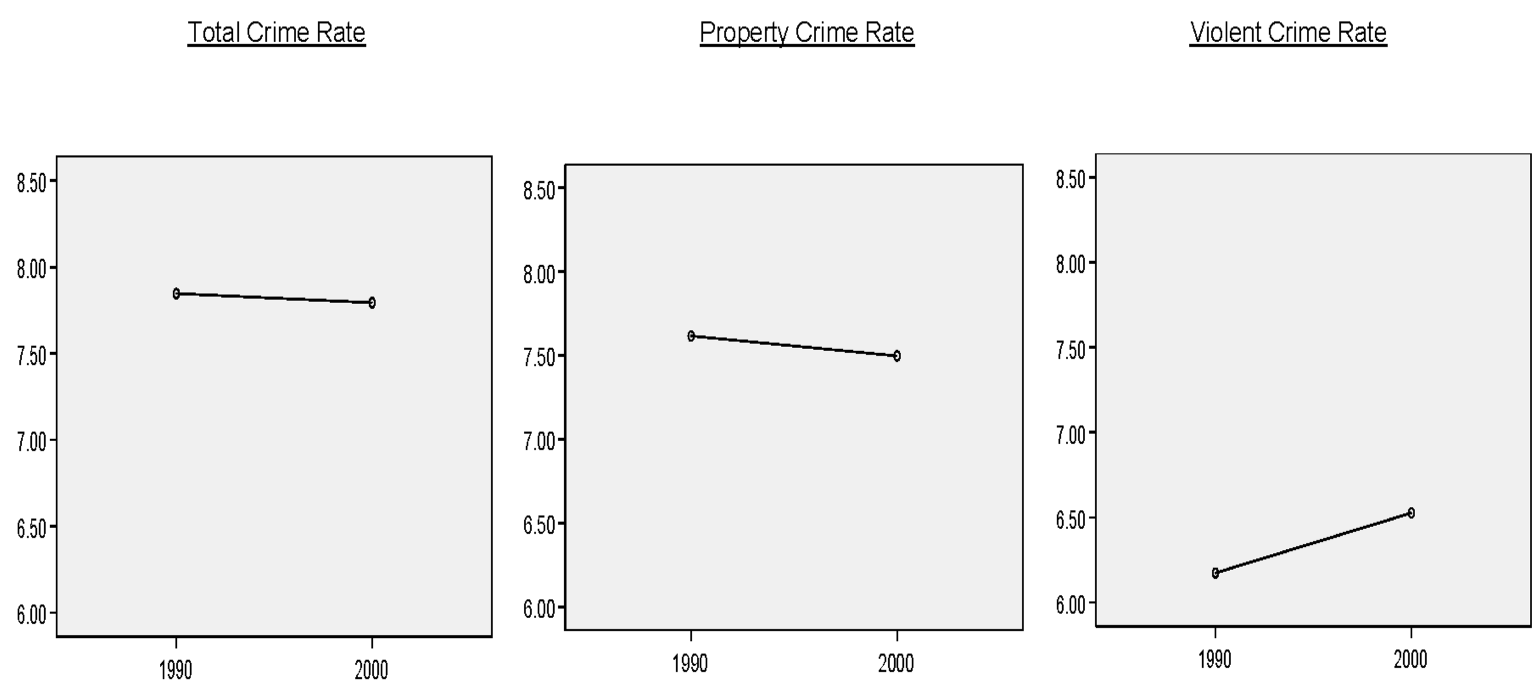
*NPT = Non-Place Territory; PLC = Place

Figure 22. Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Metropolitan Status Using a Repeated Measures ANOVA Approach, 1990 – 2000



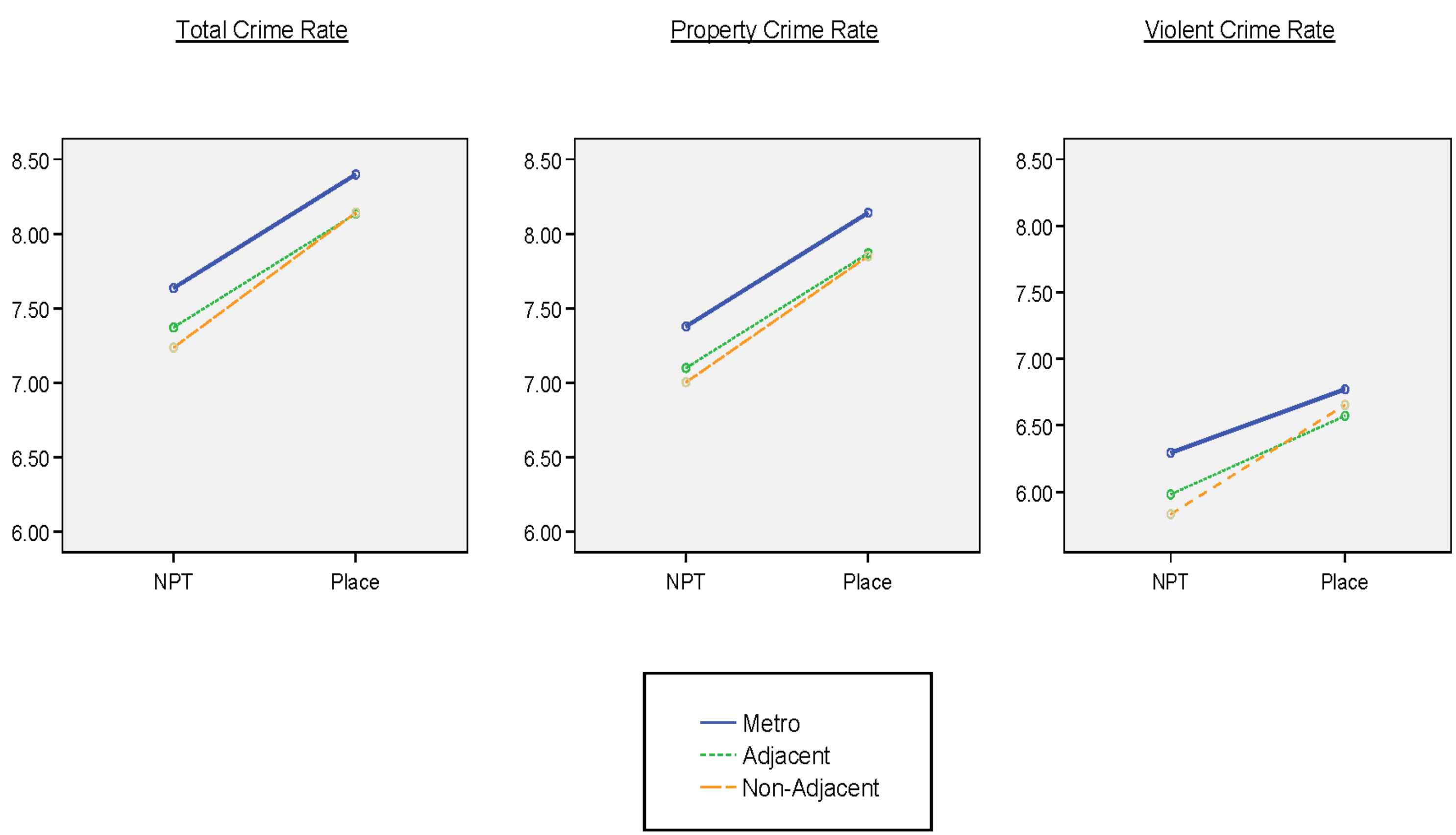
*NPT = Non-Place Territory; PLC = Place

Figure 23. Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by U.S. Census Region Using a Repeated Measures ANOVA Approach, 1990 – 2000



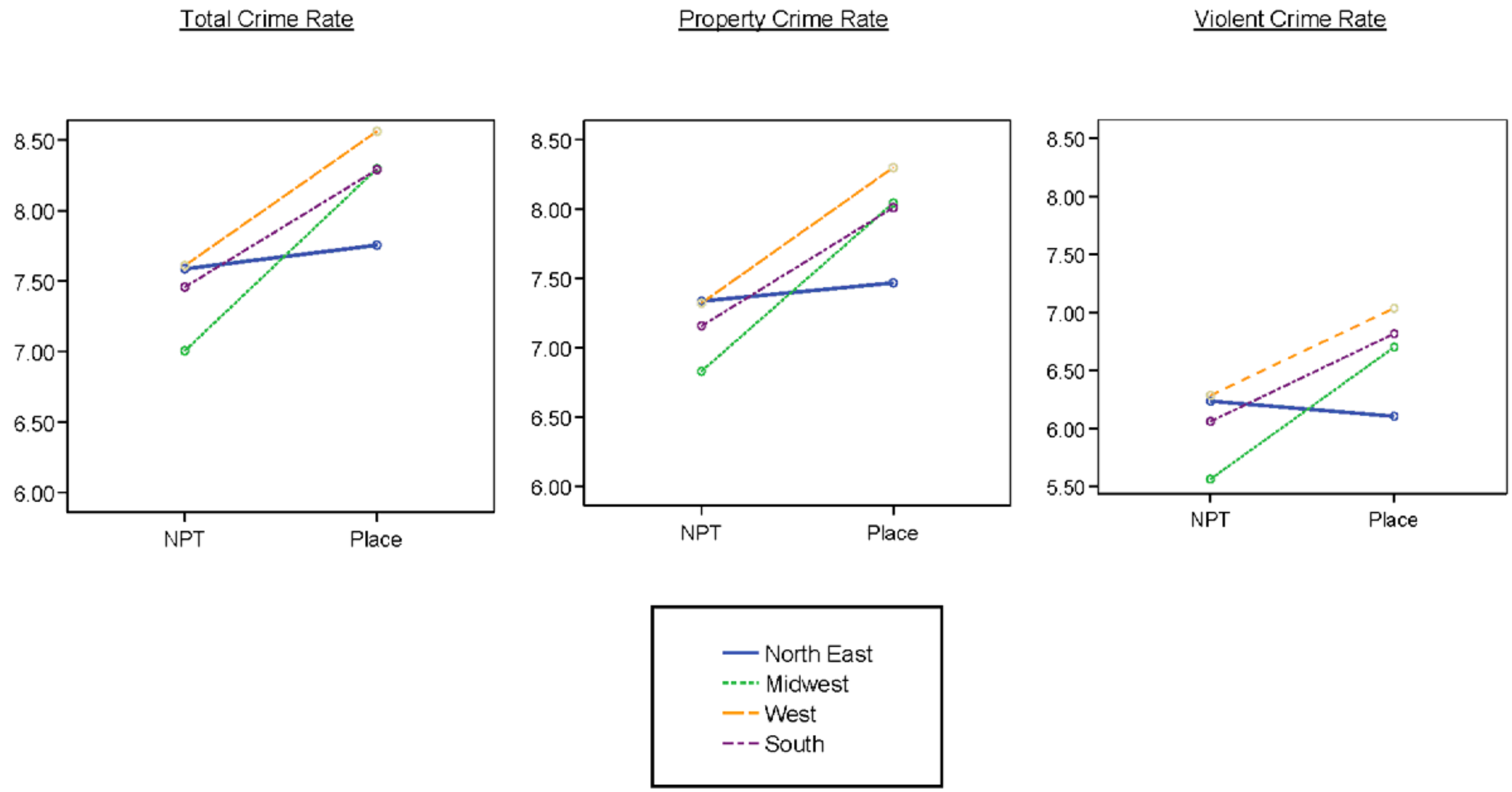
*NPT = Non-Place Territory; PLC = Place

Figure 24. Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Decade Using a Repeated Measures ANOVA Approach, 1990 – 2000



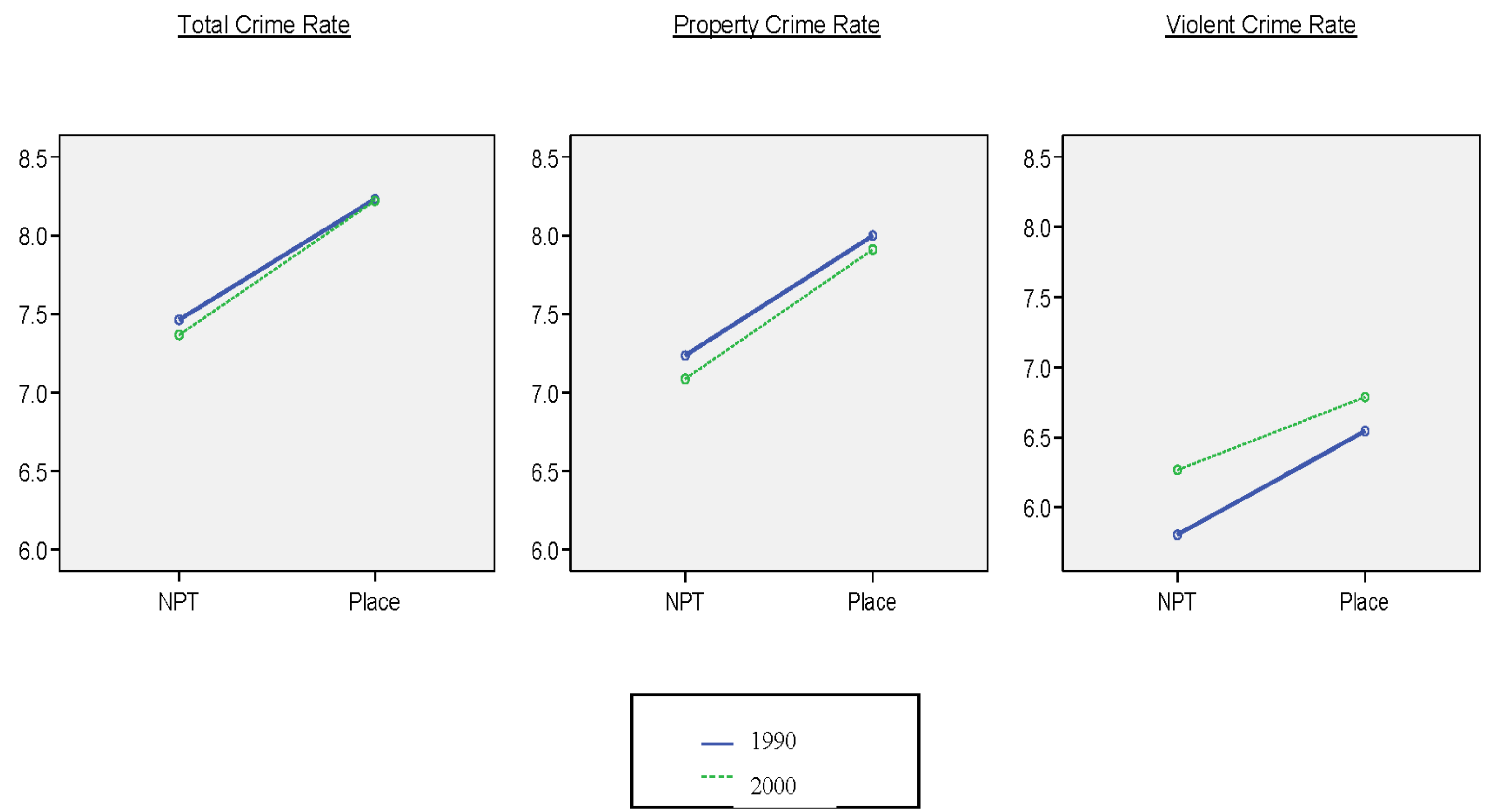
*NPT = Non-Place Territory; PLC = Place

Figure 25. Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Place-Level and Metropolitan Status Using a Repeated Measures ANOVA Approach, 1990 – 2000



*NPT = Non-Place Territory; PLC = Place

Figure 26. Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Place-Level and U.S. Census Region Using a Repeated Measures ANOVA Approach, 1990 – 2000



*NPT = Non-Place Territory; PLC = Place

Figure 27. Estimated Marginal Mean Plots of Logged Type-Specific Crime Rate by Place-Level and Decade Using a Repeated Measures ANOVA Approach, 1990 – 2000

have significantly higher rates. This is especially true in the West region. Figure 24 presents the crime rate by year. The figure shows very little difference in the total and property crime rates from 1990 to 2000, although they do trend downward slightly. However, interestingly the violent crime rate rises during the time period.

Figures 25 – 27 examine the interplay of some of these relationships through the interaction of each classifier by place-level. First, figure 25 reports the estimated marginal means for place level by metropolitan status. From the figure it seems that while the non-adjacent non-metropolitan crime rate is lowest in non-places it is equal or higher than the crime rate of places adjacent non-metropolitan localities. The biggest discrepancy involves violent crime, where the two actually cross.

Figure 26 reports the interaction of place-level and U.S. census region in relation to crime rates. Perhaps the most interesting point to be made is the fact that the rate of crime in places and non-places in the Northeast is almost identical. The rates in the other three regions are drastically different, as places have a much higher rate of crime than do non-places. All there type-specific crimes have similar patterns with the West having the highest rate in both places and non-places and the Midwest going from the lowest rate in non-places to the second highest in places.

Table 8. Trends in Type-Specific Crime Rates by Place-Level Geography

	Trends in Crime by the Percent of Cases in each Category	
Place Level Geographies	Decrease	Increase
Total Crime Rate		
Place	54.2	45.8
Non-Place	49.4	50.6
Property Crime Rate		
Place	59.3	40.7
Non-Place	61.7	38.3
Violent Crime Rate		
Place	44.8	55.2
Non-Place	31.3	68.7
Total U.S.		
Total Crime Rate	52.4	47.6
Property Crime Rate	60.2	39.8
Violent Crime Rate	39.9	60.1

Finally, figure 27 reports the interaction of place-level and temporal period. The figure plainly shows that there was not much of a difference in total crime or property crime rates in relation time, with the trajectories of the lines basically mirroring one-another. However, it seems that while the rate of crime was higher in 2000, the difference between places and non-places was greater in 1990 when examining violent crime. This is an interesting point as it suggests that places and non-places may be coming more alike as time presses forward.

Spatio-Temporal Interactions and Heterogeneity

Statistical Trends in the Type-Specific Crime Rates

As part of this examination into the differences by intersection of spatial location and temporal period, percentage of cases associated with their trends in raw change for each type-specific crime rate were examined across place-level geography in order to identify any potential trends in recent trends. From table 8, the percentage of all cases within a given place-level geography that either increased or decreased, given a specific crime rate type, are reported. For instance, 54.2 percent of all places decreased in their total crime rate over the ten year period, while 45.8 percent increased. Similarly, 59.3 percent of places decreased in property crime while only 44.8 percent of places decreased in violent crime.

Table 9. Mean Differences in Raw Change by Type-Specific Crime Rates Across U.S. Region, Metro Status, and Place-Level Geography

	Total Crime	Property Crime	Violent Crime
	Rate Change 1990-2000	Rate Change 1990-2000	Rate Change 1990-2000
Comparison Groups	Mean (F-Stat)	Mean (F-Stat)	Mean (F-Stat)
Place Level Geography			
Place	0.017	-0.065	0.271
Non-Place Territory (NPT)	-0.032	-0.111	0.536
F-Statistic	(4.087*)	(4.550*)	(116.500***)
Eta-Squared	0.000	0.001	0.014
Metropolitan Status^			
Metropolitan	-0.007	-0.082	0.321
Adjacent Non-Metropolitan	-0.009	-0.0872	0.383
Non-Adjacent Non-Metropolitan	0.026	-0.073	0.447
F-Statistic	(0.717 ns)	(0.119 ns)	(8.706***)
Eta-Squared	0.000	0.000	0.002
U.S. Region~			
Northeast	-0/232	-0.312	0.066
Midwest	-0.119	-0.149	0.271
West	0.008	-0.043	0.274
South	0.146	0.020	0.573
F-Statistic	(50.393***)	(41.151***)	(84.613***)
Eta-Squared	0.018	0.014	0.029

*** Mean difference is significant at < .001 level

* Mean difference is significant at < .05 level

^ Metropolitan and Non-Adjacent Non-Metropolitan were significantly different in terms of the rate change in violent crime rate from 1990 - 2000 while all other individual pairwise comparisons were not significantly different in terms of the rate change in violent crime from 1990 - 2000

~ Midwest an the West were not significantly different in terms of the rate of change in violent crime rates from 1990-2000 while all other pairwise

Among non-places, about as many increased as decreased in terms of the total crime rate, with about 50 percent of the cases in each category. However, there was a dramatic decrease in property crimes and an even larger number of non-places that increased in violent crime. This is consistent with processes of contiguous diffusion either through relocation or outward spread. Lastly, among both non-places and places, the total crime rate decreased in about 52 percent of the areas, while the property crime decreased in about 60 percent of the areas and the violent crime increased in about 60 percent of the areas.

The results in table 9 illustrate the mean differences by each of the classifier variables examined above in the year-static results from table 6. The results show that there is a non-significant difference in the percent change of crime across place-level geography for both the total crime rate and the property crime rate. However, there is a significant difference in the raw change in the violent crime rate as non-places grew at a much larger rate than did places.

In the middle of table 9, there were significant differences in the average percent change for all three type-specific crime rates. The largest increase in all three cases took place in the areas in non-adjacent non-metropolitan counties. Following the hierarchy the second largest increase took place in the adjacent non-metropolitan areas and the least growth took place in the metropolitan counties. This finding leads to the conclusion that if non-metropolitan areas are growing faster than metropolitan areas, there may in fact be a diffusion process of outward spatial mobility at work involving the transmission of social behavior from the core, places, to the periphery, non-places.

Lastly, the bottom section of table 9 includes the results of the differences in the percent change in type-specific crime rates by U.S. region. The results show that in all three crime rates the mean differences among regions is statistically significant based on the F-statistic. In each case the fastest growing region, in terms of crime, is the South. This may follow other demographic trends as the South has recently been the fastest growing region in terms of raw population as well, perhaps bringing with it criminal behavior. In terms of the total crime rate, the Midwest and the South were not statistically different from one another, based on the LSD multiple comparisons method, and had the second and third highest growth. This left the Northeast as having the lowest amount of growth over the time period.

In terms of property crime, following the South, the West had the second highest growth rate. This was followed by the Midwest and the Northeast, which again had the lowest percent change. The violent crime rate of the Midwest changed the second most, following the South. Again, the Northeast had the lowest rate of change. As with the metropolitan status classification, all three type-specific crime rates were significantly different as a group across all regions. As hinted at above, the Midwest and the West were not significantly different from on another across all three crime rate types and the Northeast and the West were not significantly different in terms of the percent change in the violent crime rate.

Many of these differences are shown to be significantly different from one another, which could be a product of population size. In relation, the eta-square for each category illustrates that when temporal change in crime from 1990 to 2000 is taken into account, the differences by place and non-place basically cease to exist. Also, between the years of 1990 and 2000 there was almost no variation in the raw change in the rate of crime based on metropolitan status and U.S. Census Region, with the largest amount of variation in the change in crime rate being accounted for by regional classification in relation to violent crime at about three percent. This means that, in general, as the type-specific crime rate changed it did so irrespective of the larger place-level, metropolitan status, and regional classification.

In order to examine the proposition that spatial heterogeneity exists at a more complex level than that of the group means illustrated in table 9, the raw change in crime rate was examined across the same, twenty-four category, multi-level classification system used in table 7. The results are presented in table 10. These results lend support for such a proposition; however they do not show the

Table 10. Raw Rate Changes in Type-Specific Logged Crime Rates by Spatial Categorization

Spatial Categorization		Percent of Cases	Total Crime	Property Crime	Violent Crime
			Type Specific Crime Rate (LN)*		
Northeast					
Metropolitan					
	Place	8.6	-0.267	-0.344	0.009
	Non-Place	1.5	-0.172	-0.283	0.296
Adjacent					
	Place	1.8	-0.180	-0.214	-0.031
	Non-Place	0.9	-0.113	-0.293	0.304
Non-Adjacent					
	Place	0.2	0.096	-0.032	0.049
	Non-Place	0.2	-0.617	-0.427	0.215
Midwest					
Metropolitan					
	Place	8.1	-0.097	-0.161	0.159
	Non-Place	2.6	-0.352	-0.181	0.299
Adjacent					
	Place	4.1	-0.015	-0.086	0.203
	Non-Place	4.3	-0.394	-0.309	0.218
Non-Adjacent					
	Place	3.5	-0.012	-0.129	0.275
	Non-Place	5.5	0.031	-0.055	0.510
West					
Metropolitan					
	Place	6.8	0.104	0.065	0.184
	Non-Place	1.1	0.246	0.142	0.670
Adjacent					
	Place	3.1	-0.109	-0.152	0.058
	Non-Place	2.1	-0.024	-0.077	0.484
Non-Adjacent					
	Place	1.5	-0.188	-0.242	0.107
	Non-Place	1.7	-0.106	-0.180	0.417
South					
Metropolitan					
	Place	12.4	0.126	0.032	0.485
	Non-Place	4.8	0.292	0.081	0.861
Adjacent					
	Place	9.1	0.229	0.101	0.478
	Non-Place	7.2	0.024	-0.114	0.692
Non-Adjacent					
	Place	4.1	0.205	0.098	0.493
	Non-Place	4.8	0.028	-0.098	0.585
Eta-Squared			0.029	0.023	0.045

*** Mean differences significant at less than the .001 level.

same within group spatial heterogeneity as does table 7. The results do show that when the change in the type-specific crime rate is examined across the more in-depth classification system, a good deal more variation is accounted for, via the eta-square statistic, than accounted for in table 9. In fact, as much as four and a half percent of the variation in violent crime is accounted for in this classification system, where a max of three percent was accounted for in the preceding table.

Spatial Trends in the Type-Specific Crime Rates

While these are large group averages, it is important to take a look, geographically, at exactly *where* these gains and losses took place in order to better understand the potential trends in offending over the time period. From figure 28, the geographic distribution of the percent change in the total crime rate from 1990 to 2000 in map form. The map looks to be completely random as there is not as clear a picture as there was in the earlier transformed rate and smoothed rate maps. However, subtle trends do appear upon close inspection.

For instance, there seems to be a larger amount of blue, representing percent loss, in the Midwest and Northeast. Likewise, there seems to be a greater number of red, representing percent increase, in the South and West regions.

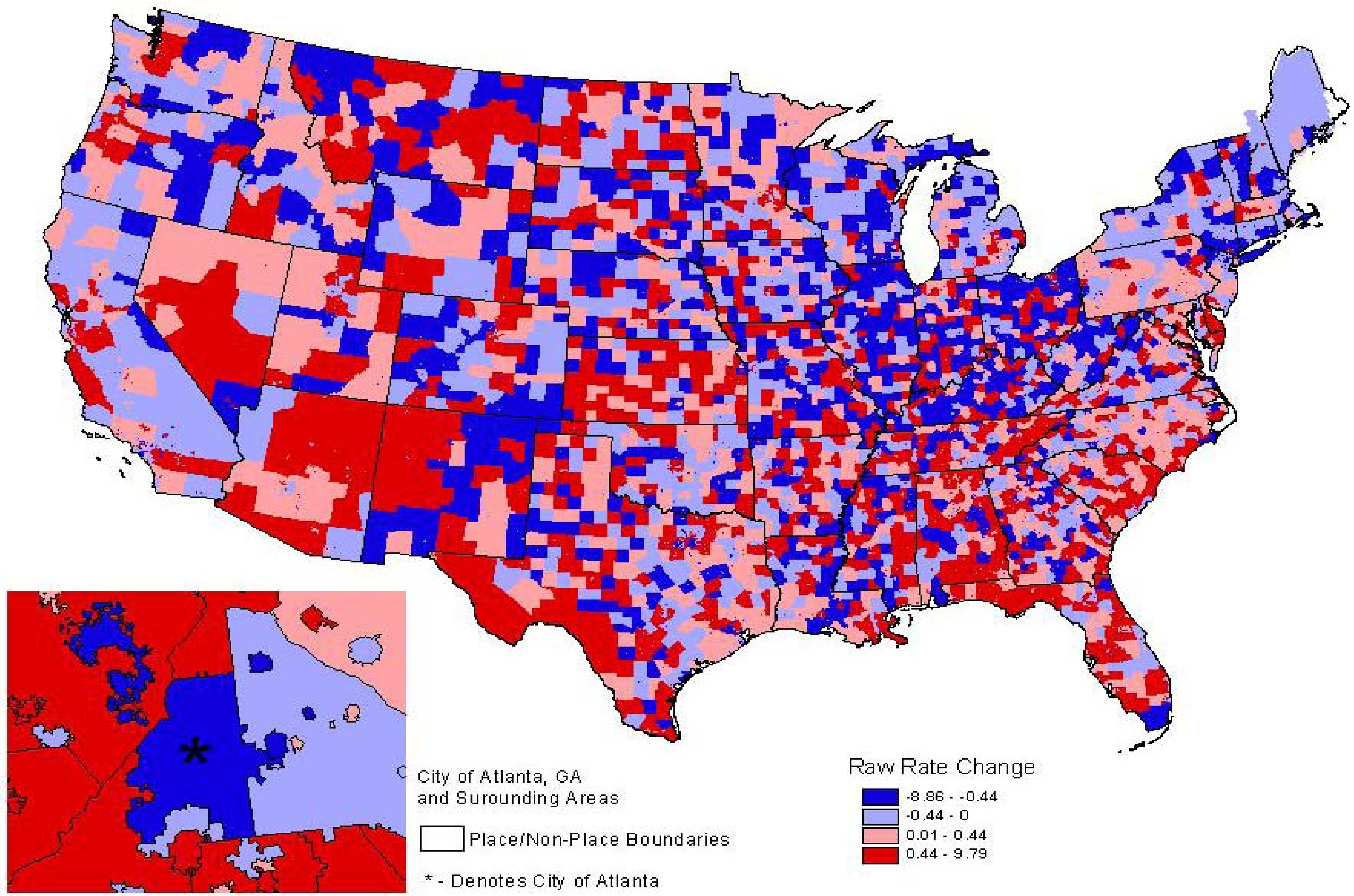


Figure 28. Raw Change in the Logged Total Crime Rate per 100,000, .1990 – 2000

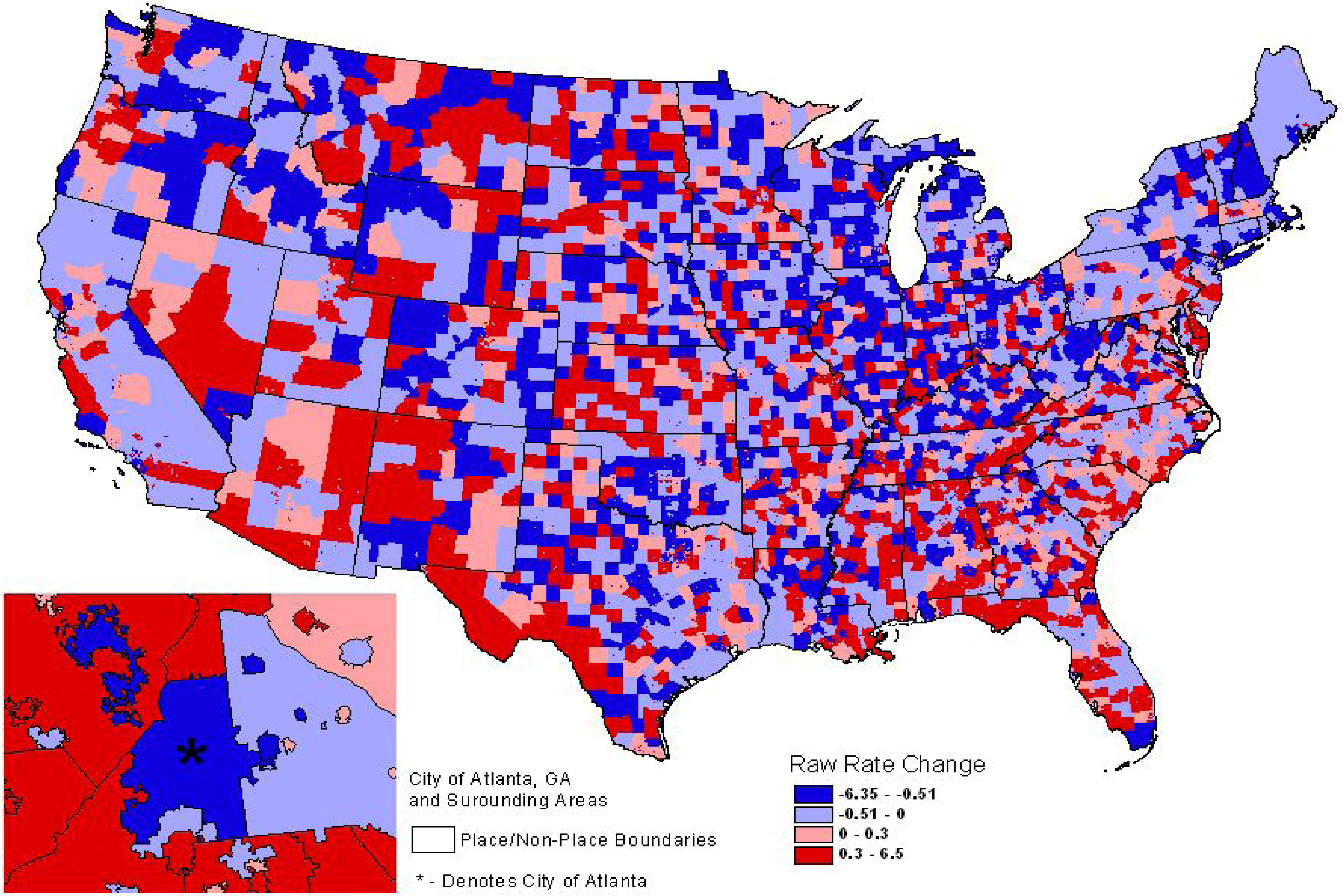


Figure 29. Raw Change in the Logged Property Crime Rate per 100,000, 1990 – 2000

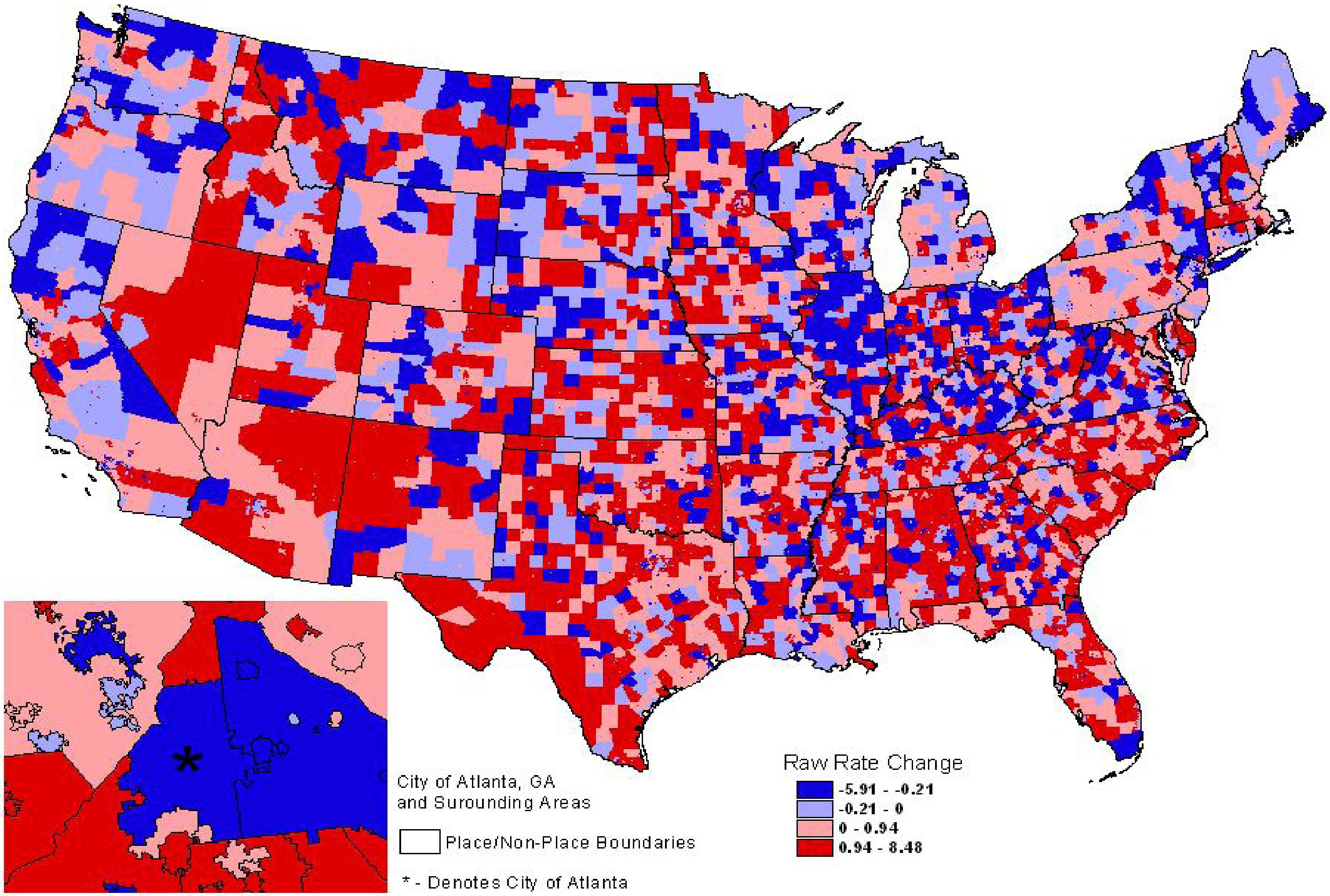


Figure 30. Raw Change in the Logged Violent Crime Rate per 100,000, 1990 – 2000

Within the inset the city of Atlanta is among those in the category of greatest decline in the total crime rate over the time period. To the East of the city, it looks like the large NPT [J: what county name?] also declined, in terms of the total crime rate from 1990 – 2000. This seems to be more of an exception than the rule, as all of the other non-places appear to have risen in their total crime rate over the time period. This may be evidence of some form of diffusion, especially some form of relocation diffusion associated with the displacement of crime from one area to another, which will be examined formally later in this project.

In terms of the raw change in property crime over the 1990 to 2000 period, the pattern seems to be even more pronounced, as evidenced by the large number of blue polygons in figure 29. There seems to be a slightly higher number of blue areas in the Northeast and Midwest, however, it is also evident that a great deal of areas in the remaining regions lowered their property crime rates as well. The largest pockets of percent gains concentrated in the South and West, especially in Texas and Florida. Similar patterns also exist in the inset concerning the city of Atlanta.

Lastly, in terms of type-specific examinations of the percent change in crime rates, the results for the change in the violent crime rate over the ten year period are presented in figure 30. In this figure there is much "redder" than in the percent change in property crime figure, figure 29. This indicates that property crime and violent crime act differently from one another and deserve to be examined as independent behaviors. In figure 30 it seems that the few areas of loss tend to be in the upper Midwest and scattered about the Northeast and northwestern portion of the country. On the other hand the areas of gain in the violent crime rate seem to be spread throughout the study region, especially in the South and West regions. In relation to the inset, it seems that the mobility of crime from the city is more pronounced, as it moves to the South, West, and North.

In order to statistically identify these pockets of significant increases or declines in crime rates over the decade, the LISA procedure (Anselin 1995) was computed on all three type-specific crime rates. The results in figure 31 illustrate the significant spatial clusters of the raw change in the total crime rate from 1990 to 2000. The global Moran's I score of 0.0357, significant at less than the 0.05 level, indicates positive clustering. This means that areas that gained in crime over the time period tended to be in neighborhoods of areas that gained in total crime over the time period.

Areas that lost tended to be in pockets of areas that also lost in terms of the total crime rate over the period. The figure shows that there were indeed clusters of areas in the upper Midwest, around Chicago, that significantly

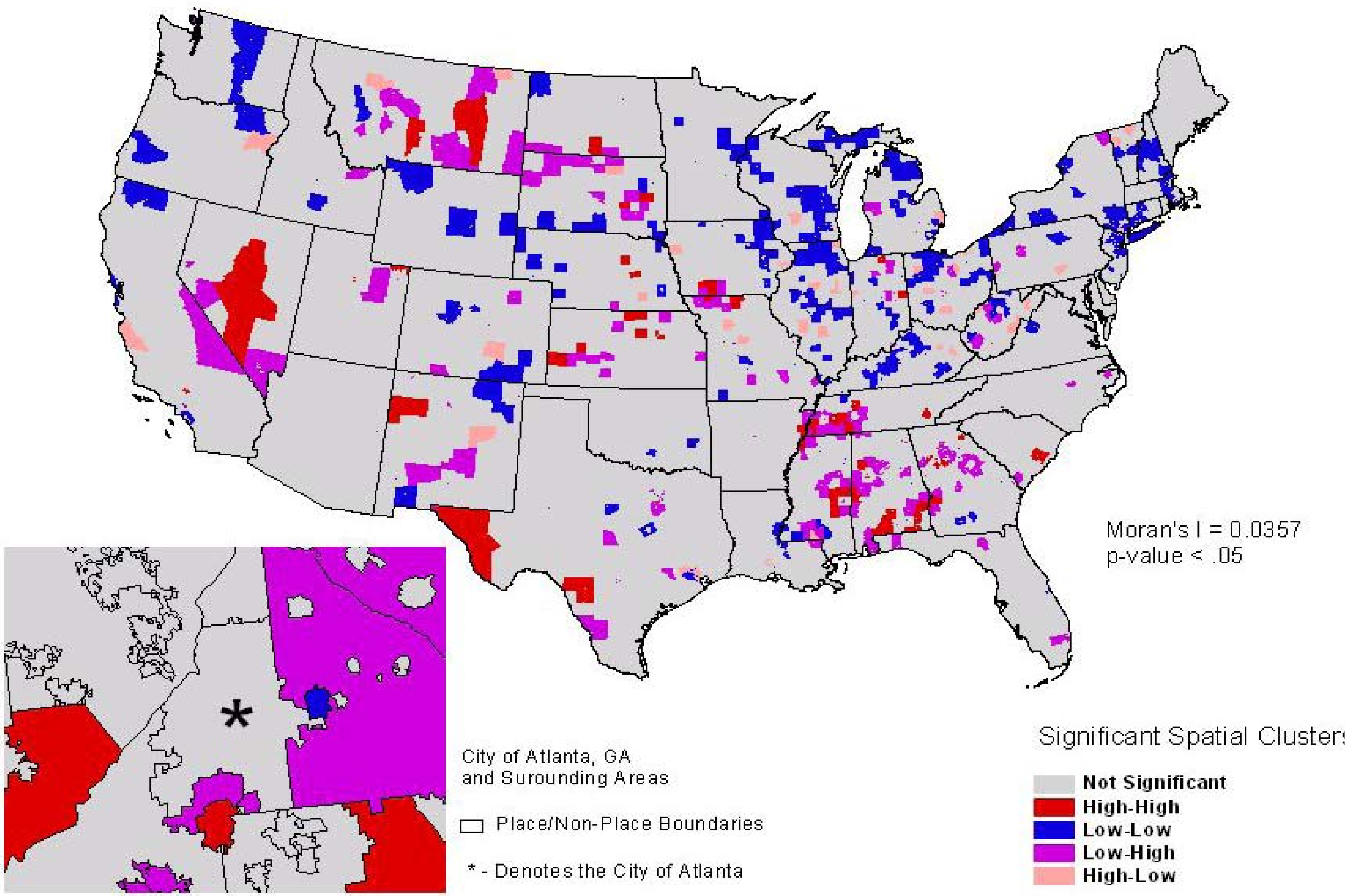


Figure 31. Significant Spatial Clusters in the Raw Change in the Total Crime Rate, 1990 – 2000

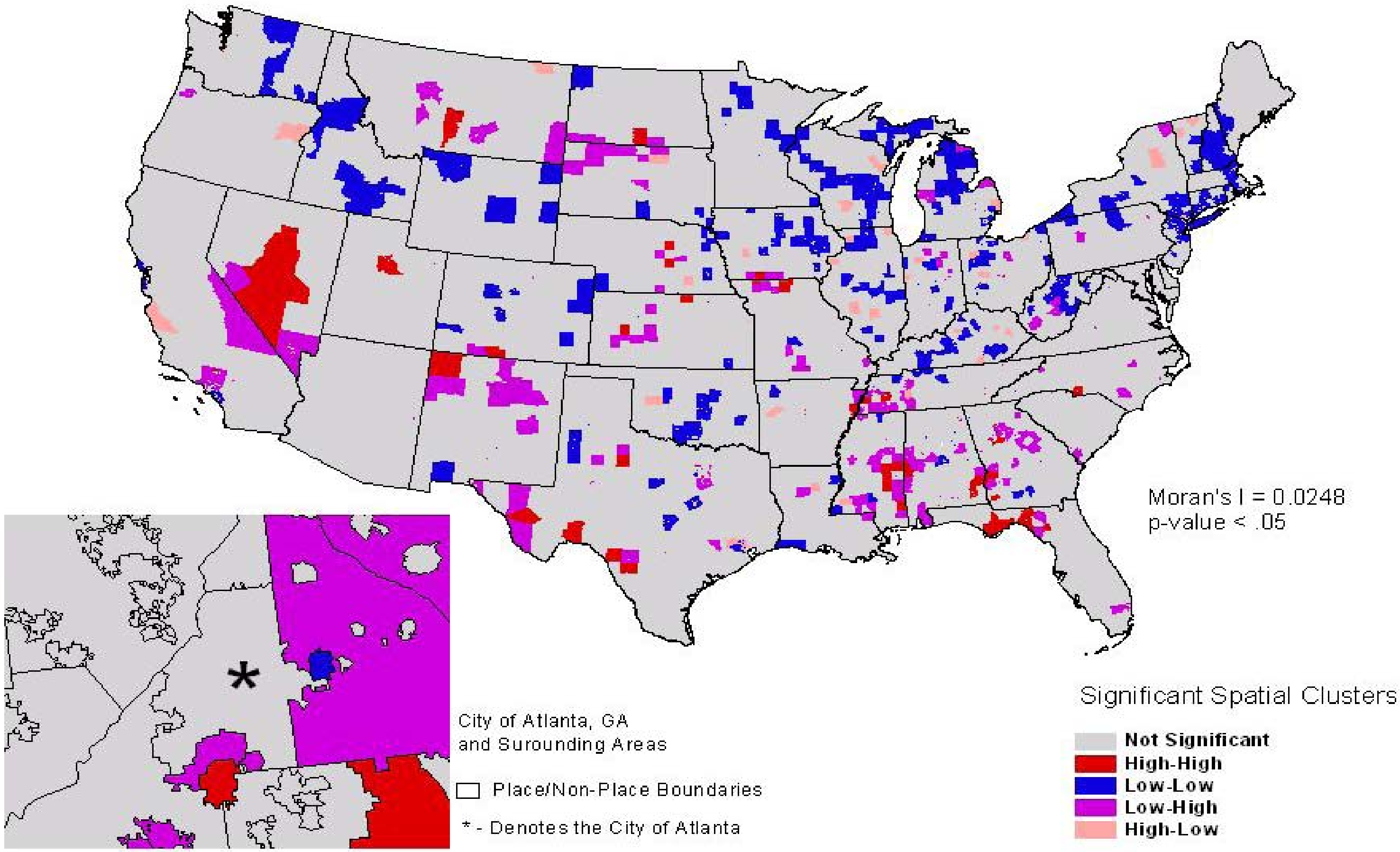


Figure 32. Significant Spatial Clusters in the Raw Change in the Property Crime Rate, 1990 – 2000

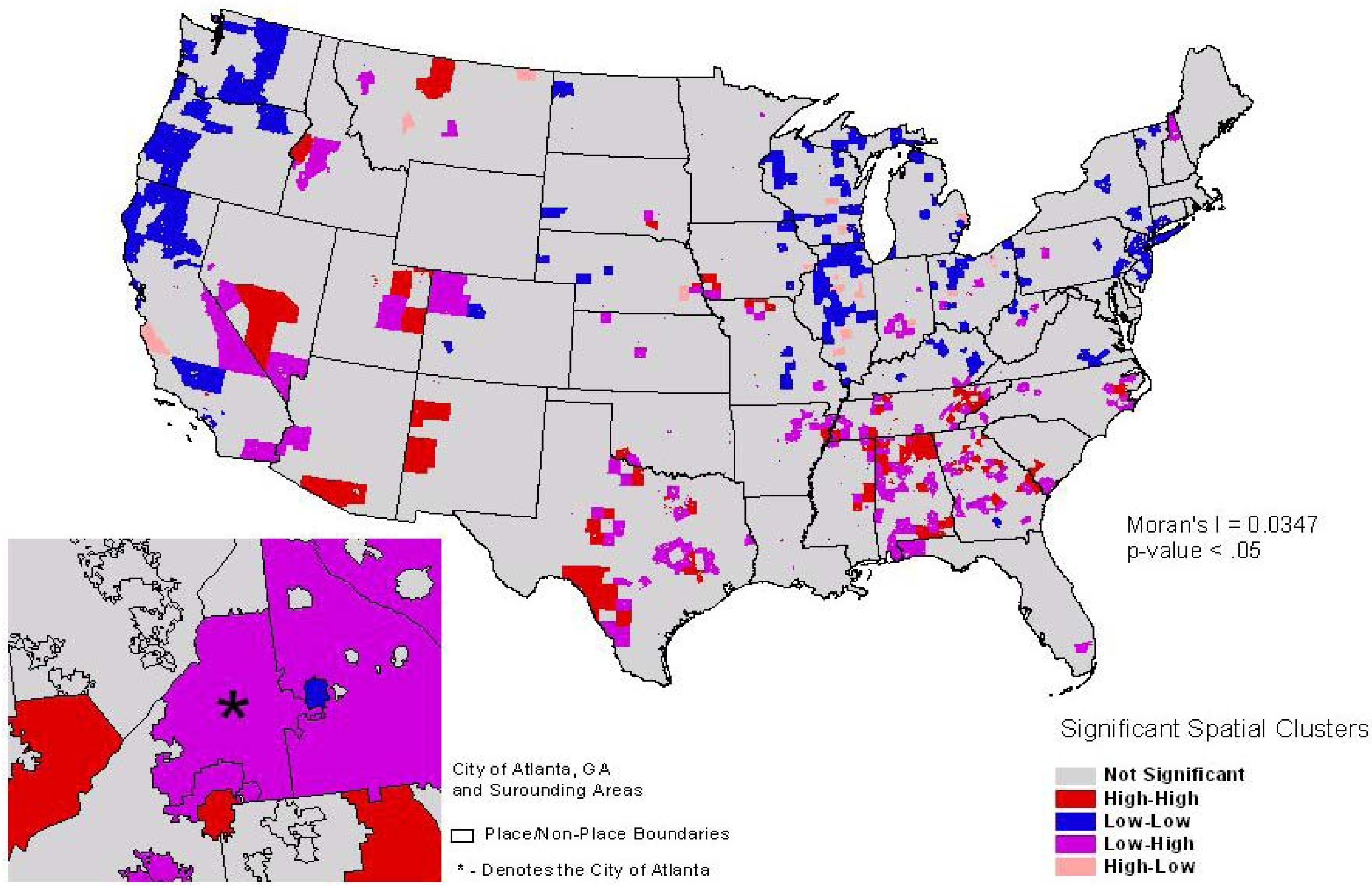


Figure 33. Significant Spatial Clusters in the Raw Change in the Violent Crime Rate, 1990 – 2000

decreased in the total crime rate over the time period. There are similar pockets in the Northeast around New York and Boston. The significant spatial clusters of high growth in the total crime rate are primarily found in the South, around Memphis, eastern Mississippi, western Alabama, parts of Texas, and Nevada. Overall, these significant spatial clusters follow the patterns identified above upon visual inspection of the percent change maps.

Within the inset, expected patterns are identified as the northeast area, around Fulton County, seems to be in a significant cluster as an area of falling crime surrounded by areas of rising crime. These undertones of crime displacement hint again at diffusion patterns over this time period. There are three distinct areas of high clusters of rising crime rates. One, to the southeast of the city and one to the west city, interestingly both are non-places. The third is an area of high crime, in a high cluster, to the south of an area that is experiencing loss in crime but is surrounded by areas of rising crime (as identified by its purple 'Low-High') classification. This place is surrounded on three sides by non-places, leading to the tentative assumption that place crime rates, in general, are decreasing, while non-place crime rates are increasing.

Finally, figures 32 and 33 illustrate the same results for the significant spatial clusters of the percent change in the property crime and violent crime rates, respectively. The global Moran's I coefficient of 0.0248, significant at less than the 0.05 level, again indicates significant positive clustering. In figure 32, there are significant decreases in the Northeast, Midwest, and northern West. Also, there are significant areas of increased property crime in the South and West. Likewise, similar patterns exist in figure 33 as the significant spatial clusters of percent increases in the violent crime rate occur in the South and West and the clusters of decline occur in the Midwest, Northeast, and the West coast. As in the above figures, the global Moran's I coefficient of 0.0347, significant at less than the 0.05 level, indicates significant positive clustering.

The previous analyses using the LISA results do not take into account the explicit proximity of places to NPTs. However, the following summary table explicitly examines these results via a cross-tabulation across the place-level geography. The results are presented in table 11. From these results, it is evident that most areas are not in any type of significant cluster, regardless of their observed trend in criminal offending. However, where significant clusters do occur, it seems that, overall, crime has declined in the ten year period, based on the highest percent of cases in the 'Low-Low category. This means that these areas were decreasing in crime along with there surrounding areas.

However, this could also mean that while crime decreases in clusters, other behaviors of crime may not happen in spatial proximity to one another. Of interest here is the fact that, across the place-level classification, places

Table 11. Crosstabulation of Spatial Clusters for Changes in Type-Specific Crime Rates by Place-Level

	Place Level Geography			
	Place		Non-Place	
Change in the Total Crime Rate	N	Percent of Places	N	Percent of Places
Not Significant	2626	84.4	4841	90.1
High - High	67	2.2	72	1.3
Low - Low	240	7.7	261	4.9
Low - High	138	4.4	155	2.9
High - Low	39	1.3	43	0.8
Change in the Property Crime Rate				
Not Significant	2637	84.8	4889	91.0
High - High	48	1.5	68	1.3
Low - Low	260	8.4	233	4.3
Low - High	132	4.2	147	2.7
High - Low	33	1.1	35	0.7
Change in the Violent Crime Rate				
Not Significant	2680	86.2	4822	89.8
High - High	90	2.9	113	2.1
Low - Low	177	5.7	191	3.6
Low - High	146	4.7	214	4.0
High - Low	17	0.5	32	0.6

consistently had a higher percent of cases in the low categories than non-places. Meaning that even if there are mixed results on the trends in type-specific crime rates by place-level, where significant clustering of temporally related changes in criminal offending occur, they tend to be associated with places having a decreasing crime rate. It is further evidence of the high level of heterogeneity that exists across the landscape concerning relationship offending patterns and spatial context.

Conclusions

From the results of this chapter, it is evident that criminal behaviors and offending interact with space quite differently across both political and legislative boundaries, real geographic space, and temporal periods. Furthermore, the traditional delineations of areas by metropolitan status and region, while significantly different, neglect to account for a good deal of within group variation. This is shown, first by the introduction of the place-level classification, which had the highest amount of variation in each of the type-specific crime rates across these large group means. Secondly, the introduction of the multi-level spatial (table 7 and 10) category further illustrated the large amount of variation which takes place within each of the place-level, metropolitan status, and region classifications and between each intersection of these classifications.

The results consistently identify trends in crime that are not only evidence of crime as being dynamic and fluid, but also evidence of a certain level of articulation between neighboring areas. This is especially true for neighboring places and non-places. The inset on many of the maps presented in this chapter of the city of Atlanta may be a case-study in that over and over again the city of lost in crime while non-places on the peripheries continued to grow. Of course, this is one of many areas and is not directly generalizable, however it does serve an important purpose in that it provides significant evidence of contiguous temporal processes involving criminal offending. When the LISA tests of significant spatial clustering were implemented similar patterns emerged, suggesting that the findings relating to the Atlanta area are not an anomaly.

Based on the results as a whole, it is evident that reported crime is a dynamic social process to which the levels vary greatly, depending on number spatial demographic factors. Thus, it is important to understand the effects of such a process in order to identify policy and programs to better deal with acts of criminal offending. It is important to build upon these initial descriptive results and involve a spatially-centered approach in the analysis. This spatial analysis will allow for the control of autocorrelation while examining the patterns of the theoretically-specified processes being modeled. Moreover, in our attempt to develop spatial mobility models aimed at the identification of diffusion and displacement processes, this approach will be a necessity. The directly preceding chapter will focus on the former while the chapter following that focuses on the latter.

CHAPTER V

EXPLANATIONS OF REPORTED CRIME IN SUB-COUNTY GEOGRAPHIES, 1990 & 2000

In the previous chapter it was evident that spatial heterogeneity exists in terms of the geographic situation of criminal offending. This was true across both metropolitan status and U.S. Census Region. However, the place/non-place delineation proved to be an even better classifier, in terms of accounting for more between group variations than either of the other two. It also became evident that the introduction of the new place-level geography may be very useful in examining criminal offending in a more sophisticated manner. For instance, this new geographic classifier, which has already been argued to be substantively superior to the current alternatives, proves to be statistically superior to the alternatives leading to the assumption that it may be better served than the current alternatives as the unit of analysis for explanatory regression modeling.

This chapter aims to implement such an examination through the modeling of reported type-specific crime at the two points in time. The chapter is interested in determining why crime occurs in certain ecological areas and not others. Furthermore, why do some types of crimes occur in certain ecological areas and not others? Lastly, do type-specific offending determinants differ, in their impact, between 1990 and 2000?

This chapter is only focused on the year specific explanation of criminal offending and trying to understand the link between ecology and offending. While temporal processes seem to certainly be evident based on the results of the preceding chapter, this chapter will focus only on static year explanation as a way of further testing the usability of the new place-level geography via an ecological framework. The next chapter in this analysis will pick up the temporal examination in a set of models interested in identifying patterns of spatial mobility and diffusion across the three type-specific crime rates from 1990 to 2000.

Meanwhile, this chapter hopes to supplement a larger goal of this dissertation in addressing an ongoing 'argument' in the criminological literature concerning the correct geographic entity associated with neighborhoods. While this current place-level geography certainly is no to be considered the 'end-all', it is expected to make a significant contribution in this area based on it's compromising mid-level situation between the over-heterogeneous county and the over-homogeneous census trace. The use of the place-level geography, then, will allow us to examine the determinants of criminal offending at this new neighborhood definition.

Regression and Spatial Diagnostics

Based on the findings of the preceding chapter, it is important to begin the development of any regression approach with spatial diagnostics in order to better understand the covariation of criminal offending with the geographic landscape. In this last chapter we found significant spatial dependence on all type-specific crime rates at both points in time. This dependence on space can be further tested in exploratory OLS regression models specified to test for such relationships via a set of spatial diagnostics. This dissertation makes use of diagnostics supplied via the software package Geoda (also available in a number of other packages), known as the Lagrange Multiplier Tests.

The Lagrange Multiplier Tests return a series of coefficients interested in identifying the type of spatial process present in each of the regression models specified. For each model all coefficients were significant, with the dominant spatial process being a spatial lag. Only one set of models, SD3 in 2000, had a dominant spatial error process present, with the rest all having the before mentioned dominant lag process. Based on the results each regression model was re-specified in order to introduce the appropriate spatial weight into the equation. Introducing a weight for spatial error into a model entails the correcting for non-random error term correlation by adding the spatial weight to the right-hand side of the equation; also known as a Simultaneous Autoregressive Model (SAR) (Cressie 1993). Likewise, the correction of a regression model with a dominant lag process entails the introduction of a spatial weight to the left-hand side of the equation based on the non-random clustering of the dependent variable; also know as a Conditional Autoregressive Model (CAR) (Cressie 1993).

Due to the evidence in the preceding chapter that 'space matters' when explaining criminal offending, and the results of the spatial diagnostics from the OLS regression runs, the results from that analysis are relegated to the Appendix. Instead this chapter will primarily be used to present the spatial regression results as specified above. However, OLS results will be briefly examined, in a mechanical/interpretive fashion, in order to quickly identify patterns in the explanation of criminal offending without controlling for space. It is important to note here that these results are to be interpreted with caution as the failure to introduce a correction for spatial dependence, where such a process exists, is likely to produce unreliable and biased statistics (Anselin 1995; Baller et al. 2001; Messner et al. 1999; Cressie 1993; Waller and Gotway 2004).

OLS Results Explaining Criminal Offending

The OLS results for explaining criminal offending by type-specific crime rate are laid out in a series of tables in the Appendix, A.2 – A.10. These tables are organized in a way so that each table examines a type-specific crime rate via one of the specified theoretical framework, for both 1990 and 2000. Since there are three difference type-specific crime rates (total, property, and violent) and three different criminological and ecologically based theoretical frameworks (social disorganization, routine activities, and an Integrated Ecological Theory), there are a total of nine tables of OLS results. These OLS results will be examined in brevity, as the focus of this chapter is concerned with the spatial regression results following these initial OLS diagnostics (see the Appendix for results from this analysis).

The first three tables, A.2-A.4, are concerned with the explanation of the logged total, property, and violent crime rates, respectively, via the social disorganization framework. Each of the tables is further broken down into the four sub-components of social disorganization, a fully specified SD model, and a fully-specified model that includes selected place-level interaction variables.

From the first sets of models, SD1 – SD4, the results of the individual components of social disorganization tend to predict crime in a theoretically expected fashion. In short, places that are more urban, more racially diverse, lower in socioeconomic status, and with a higher degree of family disruption, on average, have higher levels of all crime types. In terms of the place-level indicator and interactions, it seems that places do have significantly a higher crime rate. Also, in all cases the per capita income has a significantly lower effect in places in comparison to non-places. Finally, these results are relatively consistent across all type-specific crime rates using the social disorganization framework.

Next, tables A.5 – A.7 examine each of the type specific crime rates via the routine activities framework. Again, these tables area laid out so that models RA1 – RA3 are interested in the three components of the theoretical framework. From these models one can see that the results tend to generally support the tenants of the theoretical framework. Specifically, areas that have more suitable targets and motivated offenders do tend to have a higher crime rate. However, the lack of capable guardian component actually increases crime as a higher proportion of capable guardians are present. This supports an alternative proposition, concerning the rate of officers per one thousand residents, as some of the criminological literature argues that are with a higher policing presence are that way because of pre-existing high crime. Again, places have significantly higher crime rates and the percent black, per capita income, percent with college degree, and percent unemployed all have a larger effect in non-places, when compared to places.

The final sets of tables in this portion of the analysis concern the implementation of the integrated ecological models, A.8 – A.10. These tables are simple laid out in a fully-specified set and another with the addition of place-level indicators and interactions. From the results, the primary patterns of specific variables tend to be similar to those in the preceding tables. The results show that the places, on average, have significantly higher rates of crime across all type-specific crimes and temporal points. Also, the per capita income has a higher effect in non-places while the percent with college degree has a higher effect in places.

Spatial Results Explaining Criminal Offending

From the spatial diagnostics outlined above, and the previous chapter, it is evident that spatial processes occur in relation to reported criminal offending. However, the preceding OLS regression technique does not explicitly model neighborhoods or geographic proximity. This begs the question, "Do the OLS results reflect the composition of the geographic units in space?". Due to the identified significant spatial association, the assumption is that they do not

The results of the spatial regression analysis are presented in tables 12 – 20. The tables are organized in a fashion similar to those reporting the OLS results from the appendix, the only difference being the inclusion of a spatial parameter, as the last independent variable, and the inclusion of an Aikine Information Criteria (AIC) as a measure of goodness of fit. The AIC is introduced here due to the fact that when examining the goodness of fit, via the r-square statistic, in the spatial regression approach, the statistic is consistently inflated due to the effect of place. Therefore, it cannot be interpreted in the same fashion. The spatial parameter is introduced as the effect of the mean criminal offending rate of the larger neighborhood where the i^{th} area is contextually situated. Finally, the type of spatial model is indicated directly under the year by a 'ρ' (rho), indicating a spatial lag or conditional autoregressive model, or a 'ε' (epsilon), indicating a spatial error or simultaneous autoregressive model.

From table 12, one can see the structure of these tables, which is relatively consistent across all of the results in this section. Within the table, it looks as if the all four of the component models contain significant effects across the board. The first model, SD1, is interested in independent effect of urbanization and shows that population size decreases the total crime rate in both 1990 and 2000, while the population density of an area increases it as it grows. This is not totally unexpected, as often the fact that non-places are many times larger than places increases the chances of them having higher raw populations. However, it is also true that the population of places tend to be situated on a smaller geographic area leading to a much higher population density. Taking this approach, these results suggest that non-places, on average, have lower crime than do places.

Also in this model, a spatial parameter is introduced as the final independent variable. The coefficient presented is positive and significant for both 1990 and 2000. The interpretation of this result suggests that the average logged total crime rate of the local neighborhood is positively associated with the logged total crime rate of the given location (Waller and Gotway 2004). This is consistent with the ESDA results from the previous chapter, in which positive spatial association was uncovered.

In the second model, SD2, the racial and ethnic heterogeneity component is examined. The results show that the higher the percent black the higher the reported crime and the higher the residential segregation the lower the crime (see table 3). These results make sense as the blacks tend to live in higher proportions in places, while the residential segregation of rural non-places is higher than that of places. The spatial parameter is again significant and positive with a coefficient of similar magnitude.

Table 12. Spatial Regression Results of Logged Total Crime Rates on a Social Disorganization Theoretical Framework

	Individual Component Models - Social Diorganization Theory^								Fully Integrated SD Model		Place Indicator Interactions	
	Model SD1		Model SD2		Model SD3		Model SD4		Model SD5		Model SD6	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables	ρ	ρ	ρ	ρ	ρ	ε	ρ	ρ	ρ	ρ	ρ	ρ
Popualtion Size	-0.147***	-0.246***	--	--	--	--	--	--	-0.155***	-0.252***	-0.183***	-0.273***
Popualtion Density	0.206***	0.187***	--	--	--	--	--	--	0.211***	0.173***	0.259***	0.184***
Percent Black	--	--	0.005***	0.008***	--	--	--	--	0.002	0.007***	0.003	0.013***
Resedential Segregation	--	--	-0.563***	-0.916***	--	--	--	--	0.138**	0.182**	0.112*	0.219***
Income per Capita	--	--	--	--	-0.125*	-0.667***	--	--	-0.206***	-0.229***	-0.096	0.076
Percent College Degree	--	--	--	--	0.072***	0.141***	--	--	0.056***	0.029	0.078***	0.118***
Percent Unemployed	--	--	--	--	0.155***	0.079***	--	--	0.048***	0.026**	0.076***	0.042*
Percent Female-Head HH	--	--	--	--	--	--	0.031***	0.039***	-0.001	-0.006	-0.018*	-0.026**
Percent Divorced	--	--	--	--	--	--	0.123***	0.315***	0.067***	0.289***	0.068***	0.317***
Percent Housing Own-Occ	--	--	--	--	--	--	0.009***	-0.016***	-0.008***	-0.011***	-0.008***	-0.011***
Spatial Parameter	0.215***	0.219***	0.277***	0.232***	0.247***	0.258***	0.217***	0.209***	0.212***	0.209***	0.211***	0.204***
Place-Level Interactions												
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	--	--	0.531	3.743***
x Percent Black	--	--	--	--	--	--	--	--	--	--	0.001	-0.006*
x Percent Female-Headed	--	--	--	--	--	--	--	--	--	--	0.019*	0.022*
x Per Capita Income	--	--	--	--	--	--	--	--	--	--	-0.094*	-0.364***
x Percent College Degree	--	--	--	--	--	--	--	--	--	--	-0.029	-0.107***
x Percent Unemployed	--	--	--	--	--	--	--	--	--	--	-0.028	-0.018
Constant	6.44***	7.408***	6.047***	6.499***	4.149***	13.846***	4.665***	6.022***	7.959***	9.461***	7.101***	6.41***
R-Square	0.201	0.195	0.070	0.089	0.069	0.077	0.138	0.124	0.235	0.232	0.239	0.239
AIC	26929	28422	28270	29461	28250	29593	27585	29106	26579	28010	26545	27936

*** P-value < .001; ** P-value < .01; * P-value < .05

^ SD1 - Urbanization, SD2 - Racial Heterogeneity, SD3 - Socioeconomic Status, SD4 - Family Disruption

ρ = Spatial Lag Model (Conditional Autorregressive Model); ε = Spatial Error Model (Simulataneous Autoregressive Model)

In examining the socioeconomic status component within the social disorganization framework, model SD3 is interpreted. The results show that the logged total crime rate decreases as the per capita income rose, in 2000, and increased along with increases in the percent unemployed and the percent with a college degree. Interestingly, the effects of the level of income per capita reversed from 1990 to 2000. In 1990, higher levels of per capita income were associated with higher levels of the reported total crime rate. There is not an explanation for this reversal readily available in the literature. One explanation may be related to the shift in trends of type-specific crime over the period as property crime tended to decrease and violent crimes tended to increase in a spatial heterogeneous fashion. As with the previous models, the spatial parameters show the average neighborhood crime rate is positively associated with the crime rate of the given locality.

In the fourth and final component model, SD4, family disruption is examined as a predictor of the logged total crime rate. The model shows that crime increases as both the percent of female headed-households and the percent unemployed increase, both in 1990 and 2000. However, the results also show that explaining logged total crime rate in relation to the percent of housing owner-occupied is mixed, as the percent increases the crime rate in 1990 and decreases the rate in 2000. Again, the best explanation that can be made at this point is related to the shifts in type-specific crime trends over the time period. It is hoped that this relationship can be better teased out in the next few couple of tables as this analysis will be replicated for the logged property and violent crime rates.

In model SD5, the fully specified model, all components of social disorganization used in this analysis were introduced in order to control across each component. In general, similar results were reported while controlling for all other determinants. However, a few interesting changes occurred including the insignificant effects of the percent black in 1990, the percent with a college degree in 2000, and the percent of housing female-headed at both points in time. The mixed effects of income per capita and the percent of housing owner-occupied were both cleared up in this model as a higher logged total crime rate is associated with lower incomes per capita and a lower percent of housing owner occupied.

In the final model SD6, place-level interactions were added to the fully-specified model from SD5. The results show that, in general, similar patterns exist with the effect of income per capita becoming insignificant and actually reversing again in 2000 to be associated with higher crime rates as it increases. Also, the percent of housing in the area that is female-headed became significant in this model as higher a higher percent is associated with a lower crime rate. In terms of family disruption, one would expect this variable to increase the crime rate as it increased and as was the case in the family disruption component model (SD4). However, when controlling for all other covariates, it becomes clear that the effect is tied to some other determinant.

This model is the first time the place indicator (0 = non-place, 1 = place) is introduced to the spatial regression section, along with all other place-level interaction variables. In relation to the place indicator, places have a significantly higher crime rate than do non-places, in 2000. Unlike the results presented in the preceding OLS section, the place indicator is not significant in the explanation of criminal offending in 1990. This is a very interesting point due to the high similarity of the effects in the OLS results and preceding descriptive chapter, which both suggest that all three type-specific crime rates were higher in places than non-places in both time periods. While that may be true in terms of large group averages, it seems that when the contextual situation of a locality within a specified neighborhood is taken into account, the effect is no longer significant in 1990. In 1990, the defined neighborhood is a better predictor than the place-level.

In terms of the place-level interaction effects, and the income per capita has a smaller effect on the place crime rate than it does on that of non-places and the percent of housing female-headed has a higher effect in places than non-places in 1990. In 2000, the income per capita, the percent black, and the percent with a college degree all have a smaller effect in places than non-places. Likewise, the percent of house holds female-headed has a significantly larger effect in places than non-places. Theoretically, the effects of the socioeconomic components have a greater effect in the rural non-places. Perhaps this is associated with the relative isolation of poor rural individuals in terms of access to services and public works. Similarly, the percent black has a greater effect in non-places. On the other hand, the family disruption determinant (percent female-headed households) has a larger effect in places, perhaps due to the lack of stability at home and high level of access to criminal activity left unchecked in places.

From this table, it is evident that determinants explain the crime rate in the same fashion that they are distributed between places and non-places. For instance, places are more densely populated, have a higher percent of minorities, a higher percent with a college degree, and a higher percent of total households headed by females. Likewise, places have higher occurrences of reported crime positively associated with each of the before mentioned determinants. The R-Square statistic inflated slightly from the OLS results across the board due to the inclusion of the positively related spatial parameter, which was significant in all models with a consistent positive parameter.

Table 13. Spatial Regression Results of Logged Property Crime Rates on a Social Disorganization Theoretical Framework

	Individual Component Models - Social Diorganization Theory^								Fully Integrated SD Model		Place Indicator Interactions	
	Model SD1		ModelSD2		Model SD3		Model SD4		Model SD5		Model SD6	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables	ρ	ρ	ρ	ρ	ρ	ε	ρ	ρ	ρ	ρ	ρ	ρ
Popualtion Size	-0.149***	-0.230***	--	--	--	--	--	--	-0.155***	-0.234***	-0.182***	-0.250***
Popualtion Density	0.203***	0.187***	--	--	--	--	--	--	0.210***	0.173***	0.257***	0.177***
Percent Black	--	--	0.003***	0.006***	--	--	--	--	0.002	0.006***	0.002	0.009***
Resedential Segregation	--	--	-0.568***	-0.885***	--	--	--	--	0.136**	0.164**	0.113*	0.197***
Income per Capita	--	--	--	--	-0.139**	-0.628***	--	--	-0.195***	-0.213**	-0.103	0.106
Percent College Degree	--	--	--	--	0.080***	0.161***	--	--	0.064***	0.047**	0.088***	0.123***
Percent Unemployed	--	--	--	--	0.138***	0.076***	--	--	0.035**	0.024**	0.058**	0.030
Percent Female-Head HH	--	--	--	--	--	--	0.028***	0.034***	-0.002	-0.007	-0.015*	-0.022*
Percent Divorced	--	--	--	--	--	--	0.121***	0.296***	0.064***	0.266***	0.065***	0.293***
Percent Housing Own-Occ	--	--	--	--	--	--	0.009***	-0.016***	-0.008***	-0.011***	-0.008***	-0.011***
Spatial Parameter	0.226***	0.248***	0.284***	0.266***	0.254***	0.285***	0.229***	0.237***	0.224***	0.237***	0.223***	0.233***
Place-Level Interactions												
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	--	--	0.428	3.896***
x Percent Black	--	--	--	--	--	--	--	--	--	--	0.001	-0.004
x Percent Female-Headed	--	--	--	--	--	--	--	--	--	--	0.015*	0.015
x Per Capita Income	--	--	--	--	--	--	--	--	--	--	-0.077	-0.379***
x Percent College Degree	--	--	--	--	--	--	--	--	--	--	-0.031	-0.094***
x Percent Unemployed	--	--	--	--	--	--	--	--	--	--	-0.025	-0.006
Constant	6.229***	6.828***	5.845***	6.029***	3.820***	13.113***	4.455***	5.694***	7.649***	8.745***	6.927***	5.566***
R-Square	0.206	0.211	0.072	0.095	0.070	0.085	0.134	0.131	0.236	0.246	0.239	0.254
AIC	26636	27290	28011	28476	27999	28588	27377	28113	26321	26917	26294	26838

*** P-value < .001; ** P-value < .01; * P-value < .05

^ SD1 - Urbanization, SD2 - Racial Heterogeneity, SD3 - Socioeconomic Status, SD4 - Family Disruption

ρ = Spatial Lag Model (Conditional Autorregressive Model); ε = Spatial Error Model (Simulataneous Autoregressive Model)

Table 13 contains the results for the explanation of the logged property crime rate using the social disorganization framework. The results are somewhat similar, which is to be expected as the results of the previous chapter has shown that property crime and total crime tend to behave similarly, in terms of reported occurrences, when compared to violent crime rates. However, place-level differences in the logged property crime rate and related interactions were expected based on the literature review, which stated that property crime tends to occur in non-places disproportionately. Also in relation to the table as a whole, consistent and positive spatial effects are again found across all models.

In models SD1 – SD5, the coefficients are relatively similar to the results from the previous table, again providing evidence of the close relationship between the two type-specific crime types. However, there are noticeable differences in the place-level interactions, primarily the lack of significant effects. In 1990, only the percent of households headed by females was significant by having a larger effect in places than non-places. In 2000, only per capita income and percent with college degree have a significantly different effect across place-level, both having a lower effect in places when compared to non-places.

The fact that there are only three total significant place-level interactions, in relation to the property crime rate, suggests an unbalanced relationship between places and non-places concerning type-specific crime rates. It seems

Table 14. Spatial Regression Results of Logged Violent Crime Rates on a Social Disorganization Theoretical Framework

	Individual Component Models - Social Diorganization Theory^								Fully Integrated SD Model		Place Indicator Interactions	
	Model SD1		ModelSD2		Model SD3		Model SD4		Model SD5		Model SD6	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables	ρ	ρ	ρ	ρ	ρ	ε	ρ	ρ	ρ	ρ	ρ	ρ
Popualtion Size	-0.114***	-0.169***	--	--	--	--	--	--	-0.110***	-0.161***	-0.137***	-0.221***
Popualtion Density	0.215***	0.138***	--	--	--	--	--	--	0.214***	0.129***	0.265***	0.184***
Percent Black	--	--	0.012***	0.011***	--	--	--	--	0.006***	0.008***	0.005*	0.010***
Resedential Segregation	--	--	-0.524***	-0.655***	--	--	--	--	0.069	0.124*	0.051	0.147*
Income per Capita	--	--	--	--	-0.035	-0.787***	--	--	-0.437***	-0.451***	-0.285***	-0.137
Percent College Degree	--		--	--	0.040***	0.046*	--	--	0.039***	-0.014	0.125***	0.145***
Percent Unemployed	--	--	--	--	0.215***	0.075***	--	--	0.084***	0.026*	0.121***	0.064**
Percent Female-Head HH	--	--	--	--	--	--	0.047***	0.047***	0.002	-0.002	-0.014	-0.018
Percent Divorced	--	--	--	--	--	--	0.129***	0.389***	0.089***	0.400***	0.089***	0.433***
Percent Housing Own-Occ	--	--	--	--	--	--	0.006***	-0.014***	-0.007***	-0.009***	-0.007***	-0.008***
Spatial Parameter	0.216***	0.258***	0.268***	0.261***	0.249***	0.291***	0.209***	0.231***	0.201***	0.236***	0.207***	0.234***
Place-Level Interactions												
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	--	--	1.094**	3.919***
x Percent Black	--	--	--	--	--	--	--	--	--	--	0.003	-0.001
x Percent Female-Headed	--	--	--	--	--	--	--	--	--	--	0.017	0.015
x Per Capita Income	--	--	--	--	--	--	--	--	--	--	-0.115*	-0.372***
x Percent College Degree	--	--	--	--	--	--	--	--	--	--	-0.112***	-0.193***
x Percent Unemployed	--	--	--	--	--	--	--	--	--	--	-0.039	-0.044*
Constant	4.752***	5.675***	4.796***	5.122***	4.305***	13.983***	3.207***	4.379***	8.135***	9.473***	6.614***	6.279***
R-Square	0.175	0.134	0.082	0.093	0.088	0.099	0.168	0.141	0.235	0.191	0.241	0.205
AIC	29050	29518	30000	29914	29926	29890	29122	29430	28416	28943	28360	28798

*** P-value < .001; ** P-value < .01; * P-value < .05

^ SD1 - Urbanization, SD2 - Racial Heterogeneity, SD3 - Socioeconomic Status, SD4 - Family Disruption

ρ = Spatial Lag Model (Conditional Autorregressive Model); ε = Spatial Error Model (Simulataneous Autoregressive Model)

that the interactions identified in the previous table concerning the total crime rate, may be tied to the differences between places and non-places in relation to violent crime. This proposition will be tested in the next table as the violent crime rate is examined via the same regression models in the social disorganization framework.

Table 14 does deviate somewhat from the first two tables (12 and 13), further illuminating some of the differences in the other type-specific crime rates, especially in terms of place-level and associated interactions. However, the general patterns exist among the individual component models with higher urbanization of an area leading to a higher violent crime rate via population density (model SD1). It is worth noting that the coefficients are not as large in relation to the effects of urbanization on the total crime rate and the property crime rate. Theoretically, this could be related to the fact that often property crimes are crimes of opportunity and the more dense and area the more opportunities for criminal offending. This will be further examined in the next set of models using the routine activities framework, which is centered on a rational choice emphasis.

The place level indicator shows that the violent crime rate was significantly different by place-level in both 1990 and 2000. This is in contrast to both the total and property crime rates, which were not significantly different in terms of reported crime place-level in 1990. The coefficient associated with the place-level indicator reports that the difference was greater in 2000 than in 1990, perhaps suggesting that over time there was a development in which violent crime has disproportionately, like property crime, shifted to places. However, the literature consistently reports that the violent crime rate is higher in places than non-places, meaning that it makes sense for both the coefficient to indicate significantly higher place offending at both points in time.

The place-level interactions provide some interesting results, primarily associated with socioeconomic status. The per capita income and the percent of the area with a college degree both have larger effects in non-places, both in 1990 and 2000. Theoretically, this may be where much of the significance in the total crime interactions. The percent unemployed is another socioeconomic related variable that has a larger effect in non-places than in places, but only in 2000.

The results from the social disorganization framework show that more urban the area, higher a percent of minorities, lower the socioeconomic status, and higher the family disruption are all associated with higher reported crime rates, across all crime types. Also, places have a significantly higher rate of all type-specific crimes in 2000 and a significantly higher rate of violent crime in 1990. Within the framework, the most consistent place-level interactions are the income per capita and the percent with a college degree, suggesting that in non-places having higher levels of socioeconomic status intensify their effect on the local crime rate.

This framework is organized around the ecological effect of the larger structure associated with a locality. While this is certainly important and given the fact that some of these components contain indicators that could be agency driven, the social disorganization framework neglects to take individual rational choice into account. The next sets of models will attempt to take such a stance through the implementation of the rational choice based routine activities framework.

Tables 15 - 17 report the results of similar analyses using a routine activities framework, in which models RA1 – RA3 represent the component models, RA4 the fully-specified model, and RA5 the fully-specified model with place-level interactions. From the results reported in table 15, the component suitable target, RA1, is examined. This model shows that increases in the per capita income and the percent of housing built before 1940 both decrease the total crime rate. On the other hand, increases in the percent of the population with a Bachelor's degree, significantly increase the rate. The effect of the housing built pre-1940 is somewhat surprising as the older neighborhoods are often associated with dilapidated/crime ridden neighborhoods. However, from this point of view the newer homes could be seen as more suitable targets along with the fact that more crime is reported in areas of higher educated individuals.

In model RA2, the motivated offender component is examined as a tool for explaining the logged total crime rate. The percent black, percent below poverty, and the percent under the age of eighteen all significantly decrease the crime rate, while the percent of households headed by females, the percent unemployed, and the percent of the population between the ages of eighteen and twenty four all significantly increase the crime rate as they increase. The results here are somewhat theoretically mixed as all are expected to drive up the crime rate as motivated offenders who are disproportionately involved in criminal offending based on some form of disadvantage.

Model RA3, the lack of capable guardian component, shows that the total population decreases crime per unit increase and that population density and the rate of officers in an area increase the rate of crime. Unlike the social disorganization set of models, the total population does explain reported criminal offending as expected. Also, the density of individuals and officers significantly increases the crime rate. It would be expected that higher the population density and the rate of officers would be associated with more capable guardians. However, this may only be measuring the place-level interactions with each of these variables die to the fact that each is higher in

Table 15. Spatial Regression Results of Logged Total Crime Rates on a Routine Activities Theoretical Framework

	Individual Component Models - Routine Activites Theory^						Fully Integrated RA Model		Place Indicator Interactions	
	Model RA1		ModelRA2		Model RA3		Model RA4		Model RA5	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables	ρ	ρ	ρ	ρ	ρ	ρ	ρ	ρ	ρ	ρ
Income per Capita	-0.149**	-0.659***	--	--	--	--	-0.355***	-0.290***	-0.264**	-0.135
Percent College Degree	0.068***	0.135***	--	--	--	--	0.049***	0.045***	0.056**	0.168***
Percent Housing pre-1940	-0.003***	-0.007***	--	--	--	--	-0.007***	-0.013***	-0.009***	-0.013***
Percent Black	--	--	-0.012***	-0.006***	--	--	-0.008***	0.002	-0.002	0.008***
Percent Below Poverty	--	--	-0.015***	-0.001	--	--	-0.002	0.007*	0.001	0.010***
Percent Female-Head HH	--	--	0.068***	0.072***	--	--	0.015***	0.004	-0.026***	-0.042***
Percent Unemployed	--	--	0.036**	0.018	--	--	0.057***	0.026*	0.092***	0.052*
Percent Under 18	--	--	-0.009**	-0.016***	--	--	0.006*	-0.002	0.009**	-0.002
Percent b/w 18-24	--	--	0.009***	0.013***	--	--	0.002	0.005	0.003	0.006*
Total Popualtion	--	--	--	--	-0.050***	-0.229***	-0.058***	-0.250***	-0.108***	-0.272***
Popualtion Density	--	--	--	--	0.147***	0.185***	0.153***	0.192***	0.238***	0.221***
Officers per 1k Pop	--	--	--	--	0.437***	0.140***	0.409***	0.112***	0.419***	0.104***
Spatial Parameter	0.269***	0.233***	0.217***	0.215***	0.209***	0.211***	0.205***	0.173***	0.199***	0.167***
Place-Level Interactions										
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	-0.758	1.327*
x Percent Black	--	--	--	--	--	--	--	--	-0.007*	-0.007*
x Percent Female-Headed	--	--	--	--	--	--	--	--	0.048***	0.052***
x Per Capita Income	--	--	--	--	--	--	--	--	-0.013	-0.135*
x Percent College Degree	--	--	--	--	--	--	--	--	-0.006	-0.146***
x Percent Unemployed	--	--	--	--	--	--	--	--	-0.039	-0.035
Constant	7.093***	12.266***	5.654***	5.855***	5.651***	7.377***	8.577***	10.525***	8.229***	9.041***
R-Square	0.055	0.069	0.126	0.101	0.245	0.207	0.266	0.239	0.275	0.247
AIC	28405	29647	27705	29338	26451	28269	26229	27914	26135	27836

*** P-value < .001; ** P-value < .01; * P-value < .05

^ RA1 - Suitable Target, RA2 - Motivated Offender, RA3 - Lack of Capable Gaurdian

ρ = Spatial Lag Model (Conditional Autorregressive Model); ε = Spatial Error Model (Simulataneous Autoregressive Model)

places than in non-places. Also, from 1990 to 2000 the effect of the number of officers dropped dramatically perhaps associated with the introduction of more officers in 1990 and a lagged effect of crime in 2000. 0.

The fully-specified routine activities model, RA4, examines the effect of each component while controlling for all other determinants in the model. This specification thus compares the relative influences of each component while controlling for the effects of all other components in the model. The results report similar effects in terms of direction, with the percent black, percent below poverty, the percent of households female-headed, and the age variables all having insignificant effects in 2000. In relation to the overall framework, the suitable target and lack of capable guardian components seem to be the most powerful as they both continue to be significant controlling for all other components. Theoretically, most of the coefficients within the motivated offender component makes sense as one would expect individuals to be motivated to commit crimes against individuals of higher socioeconomic standing. In terms of the lack of capable guardian component, the results remain consistent but they seem to measuring place-level interaction as opposed to a true lack of a capable guardian.

The place-level indicator is introduced in model RA5 and surprisingly the place indicator is reverse of what would be theoretically expected in 1990. The coefficient reports that non-places had a higher total crime rate than places, although the coefficient is negative. In 2000, places significantly had a higher crime rate than non-places. While the effects were not significant in the social disorganization framework for total and property crime in 1990, they were at least in the expected direction. These results suggest that perhaps some other predictors are missing from this analysis, which may be teased out in the final set of integrated models.

In terms of the model coefficients, income per capita and the percent of the population between eighteen and twenty four are insignificant predictors of the total crime rate. However, a few interesting developments take place as the percent black and the percent below poverty both flip directions to increase crime as they increase. This is the expected direction as both indicate individuals that theoretically should be more motivated to commit crimes.

The place-level interactions report that the percent black, per capita income, the percent college graduate, and the percent unemployed all have significantly smaller effects in places than they do in non-places. Theoretically, this means that in non-places suitable targets and motivated offenders independently effect the rate offending at a higher rate. The percent of the total households that are female-headed has a significantly larger effect in places than non-places within this framework. Neighborhood rates of offending are significant predictors of an areas rate, via the spatial parameter variable, which, like in the social disorganization framework is positively and consistently significant.

Table 16 reports the results of the spatial regression examination explaining the property crime rate using the routine activities framework. All three of the component models explain similar patterns of offending when compared to the preceding model. The higher percent of new housing and college educated individuals provide more suitable targets for offending. The motivated offender component model is again weaker than the other components in this framework as it does not fit what is theoretically expected. Also, the higher a percent of the population between eighteen and twenty-four is associated with a higher level of criminal offending. In the fully specified model the percent black coefficient reverses direction to explain a higher level of crime as it increases as a percentage. The capable guardian component models shows that higher population sizes are associated with lower crime rates, but so are higher population densities and rate of officers per population are associated with higher rates of crime.

In the fully-specified model, RA5, the patterns hold controlling for all other components included in the models. The results reiterate the lack of strength associated with the motivated offender component, whose components

Table 16. Spatial Regression Results of Logged Property Crime Rates on a Routine Activities Theoretical Framework

	Individual Component Models - Routine Activites Theory^						Fully Integrated RA Model		Place Indicator Interactions	
	Model RA1		ModelRA2		Model RA3		Model RA4		Model RA5	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables	ρ	ρ	ρ	ρ	ρ	ρ	ρ	ρ	ρ	ρ
Income per Capita	-0.107*	-0.611***	--	--	--	--	-0.342***	-0.286***	-0.274**	-0.119
Percent College Degree	0.078***	0.152***	--	--	--	--	0.057***	0.065***	0.075***	0.175***
Percent Housing pre-1940	-0.003	-0.006***	--	--	--	--	-0.008***	-0.012***	-0.008***	-0.013***
Percent Black	--	--	-0.016***	-0.007***	--	--	-0.009***	0.001	-0.003	0.005*
Percent Below Poverty	--	--	-0.014***	-0.003	--	--	-0.002	0.005*	-0.002	0.008***
Percent Female-Head HH	--	--	0.069***	0.069***	--	--	0.014***	0.002	-0.019*	-0.036***
Percent Unemployed	--	--	0.018	0.015	--	--	0.044***	0.023*	0.084***	-0.040*
Percent Under 18	--	--	-0.010**	-0.016***	--	--	0.005	0.000	0.006*	-0.001
Percent b/w 18-24	--	--	0.009***	0.015***	--	--	0.003	0.007*	0.004	0.008*
Total Popualtion	--	--	--	--	-0.052***	-0.213***	-0.059***	-0.234***	-0.119***	-0.250***
Popualtion Density	--	--	--	--	0.144***	0.186***	0.150***	0.191***	0.239***	0.212***
Officers per 1k Pop	--	--	--	--	0.435***	0.143***	0.405***	0.116***	0.415***	0.108***
Spatial Parameter	0.269***	0.258***	0.228***	0.240***	0.218***	0.237***	0.215***	0.199***	0.209***	0.193***
Place-Level Interactions										
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	-0.667	1.518**
x Percent Black	--	--	--	--	--	--	--	--	-0.006*	-0.004
x Percent Female-Headed	--	--	--	--	--	--	--	--	0.039***	0.044***
x Per Capita Income	--	--	--	--	--	--	--	--	-0.004	-0.153**
x Percent College Degree	--	--	--	--	--	--	--	--	-0.019	-0.132***
x Percent Unemployed	--	--	--	--	--	--	--	--	-0.041*	-0.023
Constant	6.501***	11.315***	5.469***	5.469***	5.446***	6.803***	8.297***	9.808***	7.975***	8.210***
R-Square	0.058	0.077	0.127	0.108	0.250	0.225	0.269	0.255	0.279	0.263
AIC	28124	28642	27446	28346	26144	27142	25949	26793	25832	26716

*** P-value < .001; ** P-value < .01; * P-value < .05

^ RA1 - Suitable Target, RA2 - Motivated Offender, RA3 - Lack of Capable Gaurdian

ρ = Spatial Lag Model (Conditional Autorregressive Model); ε = Spatial Error Model (Simulataneous Autoregressive Model)

flip from significant to non-significant across the two points in time. The potential lag of the effect of officers is again evident with a mush stronger effect in 1990. When the place indicator is introduced in RA6, places and non-places are reported to not be significantly different in 1990, while the place indicators explains a significantly higher rate of crime in places in 2000.

The place-level interactions show that the percent black and the percent unemployed have a smaller effect in places in 1990 than they do in non-places. In the same year the effect of the percent female-headed households has a larger effect in places. In 2000, the income per capita and the percent of the area with a college degree both had smaller effects in places, while the percent of female headed-households again had a larger effect in places.

Table 17 reports the final set of models in the routine activities framework in an examination of the violent crime rate. Within this framework all component models are significant across all indicators in at least one time period. It seems that the application of this theory in total may be more applicable to violent crime than either of the other two types. The suitable target component again shows that areas with a higher percent of new housing and a higher percent college educated are associated with more suitable targets for violent crime offending. However, the income per capita variable is again negative, and consistently so across all models.

In the RA2, the motivated offender variables report that a higher percent of female-headed households, a higher percent of population between eighteen and twenty-four, and a higher percent unemployed both explain higher rates of violent crime. In contrast, the percent of the population under the age of eighteen and a higher percent black are both associated with lower crime rates. This somewhat interesting as the percent black is consistently linked to higher crime rates of all types, but to this point it has proven not to be a significant indicator of such a relationship.

The third and final component model, RA3, examines the lack of a capable guardian component, reporting that the higher the population sizes the more capable guardians to deter criminal offending. However, higher population density and rate of officers both explain higher rates of offending, with the same lag associated with the officers evident from 1990 – 2000.

When the place indicator and interaction variables are included in models RA6, there is an interesting deviation associated with the higher levels of violent crime offending in places compared to the discrepancy apparent in the total and property crime rate. For the first time in this set of models, the type-specific crime rate is higher in 1990 in places than in non-places. The place-level indicator is significant across all type-specific crime rate models for the year 2000, but only concerning the violent crime rate in the year 1990.

Table 17. Spatial Regression Results of Logged Violent Crime Rates on a Routine Activities Theoretical Framework

	Individual Component Models - Routine Activites Theory^						Fully Integrated RA Model		Place Indicator Interactions	
	Model RA1		ModelRA2		Model RA3		Model RA4		Model RA5	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables	ρ	ρ	ρ	ρ	ρ	ρ	ρ	ρ	ρ	ρ
Income per Capita	-0.404***	-0.766***	--	--	--	--	-0.599***	-0.442***	-0.253**	-0.253**
Percent College Degree	0.031*	0.049***	--	--	--	--	0.029*	-0.015	0.066**	0.174***
Percent Housing pre-1940	-0.002**	-0.008***	--	--	--	--	-0.005***	-0.011***	-0.006***	-0.012***
Percent Black	--	--	-0.013***	-0.004**	--	--	-0.005***	0.003*	0.002	0.005*
Percent Below Poverty	--	--	-0.012***	0.011***	--	--	-0.003	0.009***	0.007**	0.014***
Percent Female-Head HH	--	--	0.079***	0.062***	--	--	0.019***	0.008	-0.022*	-0.029**
Percent Unemployed	--	--	0.085***	0.026*	--	--	0.094***	0.027*	0.143***	0.074***
Percent Under 18	--	--	-0.001	-0.008*	--	--	0.010**	-0.004	0.015***	-0.005
Percent b/w 18-24	--	--	0.005	0.008*	--	--	-0.006*	-0.002	0.001	0.000
Total Popualtion	--	--	--	--	-0.005	-0.149***	0.004	-0.155***	-0.081***	-0.216***
Popualtion Density	--	--	--	--	0.148***	0.137***	0.159***	0.154***	0.232***	0.221***
Officers per 1k Pop	--	--	--	--	0.491***	0.162***	0.477***	0.136***	0.474***	0.123***
Spatial Parameter	0.283***	0.265***	0.211***	0.244***	0.213***	0.248***	0.212***	0.203***	0.204***	0.199***
Place-Level Interactions										
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	0.925*	1.646**
x Percent Black	--	--	--	--	--	--	--	--	-0.007*	-0.002
x Percent Female-Headed	--	--	--	--	--	--	--	--	0.047***	0.043***
x Per Capita Income	--	--	--	--	--	--	--	--	-0.151***	-0.153**
x Percent College Degree	--	--	--	--	--	--	--	--	-0.089***	-0.227***
x Percent Unemployed	--	--	--	--	--	--	--	--	-0.539*	-0.061**
Constant	8.297***	12.364***	3.811***	4.323***	3.829***	5.628***	8.624***	10.263***	3.452***	8.382***
R-Square	0.064	0.092	0.154	0.118	0.219	0.148	0.263	0.194	0.269	0.208
AIC	30183	29934	29269	29666	28580	29371	28112	28891	28048	28745

*** P-value < .001; ** P-value < .01; * P-value < .05

^ RA1 - Suitable Target, RA2 - Motivated Offender, RA3 - Lack of Capable Gaurdian

ρ = Spatial Lag Model (Conditional Autorregressive Model); ε = Spatial Error Model (Simulataneous Autoregressive Model)

In 1990, the place interaction variables all prove to be significantly different by place-level. The percent black, income per capita, percent with a college degree, and the percent unemployed all have a significantly larger effect in non-places, while the percent of all households that are female-headed has a larger effect in places. Similar results are found in 2000, with the lone exception being the insignificant difference by place level of the percent black.

After reviewing the results from both the social disorganization and routine activities framework a few things are evident. First, across both theoretical frameworks the difference in reported crime was not significantly different by place-level in 1990 for reported rates of total and property crimes. There was a significant difference in 2000 for both types and in 1990 and 2000 for the violent crime rate. Relating this to the literature it seems that there is a qualitative difference in the types of crime that occur in places and non-places and that difference seems to be that violent crime is much more of an urban/core occurrence.

Secondly, in both sets of models the spatial parameter variable is significant and positive. Meaning that the geographic situations of individual localities are closely tied to its defined neighborhood, at least in terms of criminal offending. The two frameworks were compared in initially to test for any differences between structural and rational choice determinants of offending.

From the model is seems that there is a lot of overlap between the two, which can hopefully be teased out in the last set of models.

Tables 18 - 20 represent the results of the Combined Ecological framework, in which the components of the social disorganization and routine activities framework are married together in an integrated fashion. These models will test the effects of each of the determinants introduced in the first two sets of models as a way of controlling for both the structural and individual-level indicators of criminal offending in one combined ecological model.

The results from table 18 show that the population size, percent of households female-headed, the percent of housing owner-occupied, and the percent of housing built prior to 1940 all have a negative effect on the total crime ate as they increase. While the percent of household's female-headed is somewhat surprising based on earlier results, the percent of housing owner-occupied and the percent of housing pre-1940, both indicate more stable and "new" neighborhoods in which lower crime is expected. Even controlling for the rest of the covariates, the population size of an area still has a negative effect on crime, again suggesting that the raw population size is not a good proxy of urbanization using this place-level geography.

A locality's population density, percent black, residential segregation, percent divorced, the rate of officers, and the percent of the population under

Table 18. Spatial Regression Results of Logged Total Crime Rates on an Integrated Ecological Theoretical Framework

	Model		Interactions	
	Model FI1		Model FI2	
	1990	2000	1990	2000
	ρ	ρ	ρ	ρ
Independent Variables				
Popualtion Size	-0.125***	-0.299***	-0.179***	-0.338***
Popualtion Density	0.165***	0.163***	0.248***	0.208***
Percent Black	-0.001	0.007***	0.005*	0.014***
Resedential Segregation	0.309***	0.293***	0.289***	0.306***
Income per Capita	-0.313***	-0.195*	-0.202*	0.014
Percent College Degree	0.024*	0.015	0.011	0.094**
Percent Unemployed	0.026*	0.015	0.060**	0.032
Percent Female-Head HH	-0.001	-0.014**	-0.035***	-0.051***
Percent Divorced	0.037***	0.306***	0.041***	0.331***
Percent Housing Own-Occ	-0.009***	-0.013***	-0.008***	-0.012***
Percent Housing pre-1940	-0.006***	-0.009***	-0.007***	-0.009***
Percent Below Poverty	0.003	0.001	0.006*	0.004
Percent Under 18	0.008*	0.011**	0.009**	0.012**
Percent b/w 18-24	0.002	0.008**	0.004	0.010***
Officers per 1k Pop	0.402***	0.086***	0.409***	0.079***
Northeast	0.047	-0.288***	0.067	-0.305***
Midwest	0.247***	0.043	0.257***	0.033
West	0.249***	0.181***	0.288***	0.160***
Adajcent Non-Metro	-0.267***	-0.298***	-0.273***	-0.288***
Non-Adajcent Non-Metro	-0.315***	-0.392***	-0.319***	-0.395***
Spatial Parameter	0.178***	0.139***	0.173***	0.136***
Place-Level Interactions				
Place Indicator (1 =Place)			-0.138	1.866***
x Percent Black			-0.006*	-0.008**
x Percent Female-Headed			0.041	0.042***
x Per Capita Income			-0.060	-0.214***
x Percent College Degree			0.022	-0.085***
x Percent Unemployed			-0.037	-0.021
Constant	9.234***	10.354***	8.716***	8.398***
R-Square	0.288	0.271	0.300	0.278
AIC	25969	27550	25873	27478

*** P-value < .001; ** P-value < .01; * P-value < .05

ρ = Spatial Lag Model (Conditional Autorregressive Model); ε = Spatial Error Model (Simulataneous Autoregressive Model)

twenty four all significantly increase the total crime rate as they increase. While these determinants all theoretically explain rate of reported crime in the expected fashion here, this was not always the case in the independent SD and RA models (see the preceding results). Borrowing from each of the two frameworks, the population density increases crime as is expected in the urbanization component. The percent black and the residential segregation of an area both increase crime as expected from the racial and ethnic heterogeneity component of the social disorganization framework. Likewise the effects of community-level family disruption and individual-level motivated offender components are evident with the effects of the percent divorced and population under the age of twenty-four explain criminal offending in an expected fashion.

When examining the place-indicator variable, it is evident that, even in this integrated form, the effects of place-level are only significant in 2000 for the total crime rate. In terms of the associated place-interaction variables, the only significant effect in 1990 is associated with the smaller effect of the percent black in places. In 2000, this effect remains but is joined by significant effects of income per capita, the percent with a college degree, and the percent of female-headed households, with the latter being the only one having a larger effect in places.

In terms of regional variation, the literature and descriptive results suggest that the West and South consistently have higher rates of crime than do the other regions. Based on these two points, the South was delineated the reference category in which all regional dummies are to be compared. Not surprisingly the Northeast is significantly lower in crime than the South, while the Midwest and the West are significantly higher, controlling for all other variables in the models. The effects of the Northeast and the West are somewhat expected. However, the higher rate of crime in the Midwest is not.

Likewise, metropolitan proximity was dummy coded into two dichotomous variables, with metropolitan being the reference category. This was also done based on the literature and previous analyses that overwhelmingly say that crime occurs in urban areas more than rural areas. From the results the non-metropolitan areas are significantly lower than those classified as metropolitan, net all other variables in the model for both points in time. Finally, the spatial parameter variable is again significant across all models.

Table 19 presents the results of examination of property crime using the same integrated model approach. Again, the percent of households female-headed, the population size, percent of housing owner-occupied, and the percent of housing pre-1940 all have negative effects on the property crime rate. While the population density, residential segregation, percent black (only in 2000), percent divorced, and the percent under the age of 24 all have a positive effect on the property crime rate.

Table 19. Spatial Regression Results of Logged Property Crime Rates on an Integrated Ecological Theoretical Framework

	Model		Interactions	
	Model FI1		Model FI2	
	1990	2000	1990	2000
	ρ	ρ	ρ	ρ
Independent Variables				
Popualtion Size	-0.125***	-0.278***	-0.178***	-0.311***
Popualtion Density	0.165***	0.165***	0.245***	0.203***
Percent Black	-0.001	0.007***	0.004	0.012***
Resedential Segregation	0.305***	0.262***	0.288***	0.272***
Income per Capita	-0.291***	-0.174*	-0.205*	0.045
Percent College Degree	0.032**	0.033*	0.027	0.099***
Percent Unemployed	0.019	0.012	0.046*	0.018
Percent Female-Head HH	-0.001	-0.014**	-0.031***	-0.043***
Percent Divorced	0.032***	0.279***	0.036***	0.303***
Percent Housing Own-Occ	-0.009***	-0.013***	-0.008***	-0.013***
Percent Housing pre-1940	-0.006***	-0.009***	-0.007***	-0.010***
Percent Below Poverty	0.003	0.001	0.006*	0.003
Percent Under 18	0.006	0.010**	0.008*	0.011**
Percent b/w 18-24	0.003	0.009***	0.005	0.012***
Officers per 1k Pop	0.396***	0.093***	0.406***	0.086***
Northeast	-0.004	-0.261***	0.011	-0.275***
Midwest	0.235***	0.145***	0.244***	0.137***
West	0.214***	0.209***	0.249***	0.192***
Adajcent Non-Metro	-0.266***	-0.265***	-0.270***	-0.254***
Non-Adajcent Non-Metro	-0.314***	-0.374***	-0.319***	-0.373***
Spatial Parameter	0.187***	0.159***	0.183	0.156***
Place-Level Interactions				
Place Indicator (1 =Place)	--	--	-0.487	2.029***
x Percent Black	--	--	-0.006*	-0.006*
x Percent Female-Headed	--	--	0.036***	0.033***
x Per Capita Income	--	--	-0.039	-0.229***
x Percent College Degree	--	--	0.013	-0.072**
x Percent Unemployed	--	--	-0.033	-0.007
Constant	8.888***	9.576***	8.529***	7.514***
R-Square	0.289	0.29	0.298	0.297
AIC	25698	26375	25611	26307

*** P-value < .001; ** P-value < .01; * P-value < .05

ρ = Spatial Lag Model (Conditional Autorregressive Model); ε = Spatial Error Model (Simulataneous Autoregressive Model)

The regional discrepancies are again surprising as only the Northeast region is significantly lower than the South. In terms of the metropolitan status discrepancies, areas within non-metropolitan counties have significantly lower crime rates than the metropolitan reference group, net all other variables in the model. These geographic effects do not vary from the total crime rate presented in the preceding table; however the total and property crime rates have consistently 'behaved' similarly. The next table, examining the violent crime rate, is where differences are expected to be identified.

Like the total crime rate, only in 2000 is the place-indicator variable significant. Meaning that, place-level criminal offending rates, in regards to property crime, were not significantly different in 1990. The percent black, the per capita income, and the percent with a college degree all have a smaller effect in places than they do in non-places, while the percent of households female-headed has a larger effect in places than they do in non-places. This suggests that within places the effect of having a proportion of all households that are headed by females leads to a higher property crime rate than would be the case in non-places.

The final table in this regression analysis is table 20, which reports the results of the examination of violent crime via the integrated ecological model. From the results one can see that the percent of households female-headed, the

Table 20. Spatial Regression Results of Logged Violent Crime Rates on an Integrated Ecological Theoretical Framework

	Model		Interactions	
	Model FI1		Model FI2	
	1990	2000	1990	2000
	ρ	ρ	ρ	ρ
Independent Variables				
Popualtion Size	-0.059***	-0.191***	-0.111***	-0.267***
Popualtion Density	0.175***	0.127***	0.258***	0.211***
Percent Black	0.005**	0.008***	0.009***	0.011***
Resedential Segregation	0.252***	0.209***	0.231***	0.215***
Income per Capita	-0.508***	-0.395***	-0.364***	-0.137
Percent College Degree	-0.004	-0.025	0.035	0.124***
Percent Unemployed	0.062***	0.020	0.103***	0.059**
Percent Female-Head HH	-0.001	-0.012*	-0.034***	-0.043***
Percent Divorced	0.056***	0.148***	0.061***	0.445***
Percent Housing Own-Occ	-0.009***	-0.009***	-0.008***	-0.009***
Percent Housing pre-1940	-0.003**	-0.006***	-0.005***	-0.007***
Percent Below Poverty	-0.004	0.002	0.007*	0.007*
Percent Under 18	-0.013***	0.014***	0.014***	0.015***
Percent b/w 18-24	-0.003	0.005	-0.001	0.008*
Officers per 1k Pop	0.454	0.113***	0.451***	0.102***
Northeast	0.051	-0.348***	0.055	-0.382***
Midwest	0.258***	-0.025	0.257***	-0.041
West	0.341***	0.114*	0.356***	0.090
Adajcent Non-Metro	-0.240***	-0.272***	-0.237***	-0.249***
Non-Adajcent Non-Metro	-0.231***	-0.312***	-0.237***	-0.307***
Spatial Parameter	0.189***	0.174***	0.185***	0.174***
Place-Level Interactions				
Place Indicator (1 =Place)	--	--	-0.024	2.293***
x Percent Black	--	--	-0.004	-0.004
x Percent Female-Headed	--	--	0.037***	0.034**
x Per Capita Income	--	--	-0.062	-0.242***
x Percent College Degree	--	--	-0.046*	-0.172***
x Percent Unemployed	--	--	-0.049*	-0.050*
Constant	8.574***	9.687***	7.485***	7.15****
R-Square	0.284	0.223	0.291	0.238
AIC	27859	28577	27790	28425

*** P-value < .001; ** P-value < .01; * P-value < .05

ρ = Spatial Lag Model (Conditional Autorregressive Model); ε = Spatial Error Model (Simulataneous Autoregressive Model)

population size, percent of housing owner-occupied, and the percent of housing pre-1940 all have negative effects on the violent crime rate. While the population density, residential segregation, percent black, percent divorced, and the percent under the age of 24 all have a positive effect on the property crime rate. This is not unlike the previous two analyses of the total and property crime rate, leading to the assumption that the determinants of the types of crime are very similar.

In terms of regional variation, again the Northeast has a significantly lower rate of violent crime than does the South. However, the West and the Midwest are not significantly different from the South region. This is a deviation from the total and property crime rates where they were both significantly higher, in terms of crime rate, when compared to the South. There is no such deviation in regards to the metropolitan proximity as localities within non-metropolitan counties continue to have significantly lower crime rates than their counterparts in metropolitan counties.

For the first time the place-indicator variable is not significant concerning the violent crime rate. In both the social disorganization and routine activities framework, the violent crime rate was significantly higher in places than non-places in both 1990 and 2000. However, that is not the case here as the coefficient is not significant, and is actually negative. Places do have a significantly higher rate than non-places in 2000. The interaction variables show that income per capita, percent with a college degree, and percent unemployed all have smaller effects in places than non-places. While, the percent of households female-headed again has a greater effect in places.

Conclusions

From these results it is evident that this new geography is an adequate substitute for the traditional county-level analyses, as, for the most part, the results tend to support related criminological based theoretical frameworks. While the individual component models and theoretically specific results did not vary greatly between the spatial and OLS models, they did predict criminal offending in the expected and hypothesized direction. The biggest deviation between the OLS and spatial results was related to the place indicator variable, which lost in magnitude by proportionately huge amount when the spatial neighborhood mean was introduced as a parameter.

While there is moderate support for both the social disorganization and routine activities theoretical frameworks across all type-specific crime rates, the integrated model proved to be both the most powerful and the most efficient. The former is based on the r-square, which reached 0.030, while the latter is based on the fact that the lowest AIC statistic can be found in that set of models. Theoretically, this model suggests that the two frameworks are not competing, but instead complimentary and help to control for factors not taken into account by their counterpart.

Furthermore, it is evident that places and non-places differ in criminal offending rates, especially in 2000, with this difference being strongest in relation to the violent crime rate, as the difference is significant in both 1990 and 2000. This difference by type-specific rates and temporal period leads to the assumption that there are temporal processes at play and that they may not be exactly the same across all type-specific criminal offending.

In the next chapter these temporal processes will be examined in greater detail, as methods of diffusion and spatial mobility are implemented as a way of identifying potential areas of mobility in type-specific criminal offending. It is expected that these patterns will not be random nor will they be the same for all crime types. Therefore, localized patterns will be examined in detail to try an get a better understanding of the relationship between space, time, and reported criminal offending.

CHAPTER VI

IDENTIFYING SPATIAL MOBILITY IN REPORTED CRIME THROUGH PLACE TO NON-PLACE DIFFUSION, 1990 - 2000

From the previous two chapters, the results have shown that when implementing the sub-county geography as the ecological units for the analysis of reported crime, significant spatial processes and place-level differences exist. The significant spatial processes were identified in Chapter VII using a series of maps and exploratory spatial statistics. These initial patterns of spatial dependence set the stage for the remainder of the analysis, in which spatially-centered methods were used to predict criminal offending and identify temporal patterns of diffusion. The results from Chapter IV found that when using the sub-county geography, the theoretical determinants of crime, in general, influence type-specific criminal offending in an expected pattern.

This chapter aims to build upon those results and existing spatial analytical tools to identify areas of the U.S. in which significant patterns of potential diffusion may be identified. This diffusion is expected to exist based on the hierarchical, core-periphery relationship, of places and their non-place counterparts. Within this relationship the place, or seed, has a given behavior related to criminal offending which, in some cases, will spread outward into the surrounding non-place territory. This relationship is outlined in a core-periphery context by Lightfoot and Martinez (2000) and in a more general context by Agnew (1993). Based on their arguments, and given a time lag, if diffusion has taken place then the non-place should have similar behaviors concerning the criminal offending at time two (t2) compared to the places within it's borders at time one (t1).

Identifying Within-County Neighborhoods

Up to this point, the spatially-centered methods have been interested in general ecological closeness, identified by a "queen-matrix" definition. While this definition is interested in all localities that share a common border, the identification of place to non-place diffusion requires a definition aimed at maximizing the within-county connectivity. For this purpose a *k* nearest neighbors approach will be employed[10]. By aggregating (summing) the number of places within a given county and computing simple descriptive statistics on that count, it is possible to identify potential *k's* to be used in the definition of the within county neighborhoods. The range of places within a county varies greatly from zero to seventy-seven, with a mean of 2.75, a median of 2.34, and a standard deviation of 3.01. However, they concentrate between two and four, with seventy percent of the counties having two places, eighty-one percent having two or three places, and eight-seven percent having between two and four places.

Ultimately, three was chosen as the number of nearest neighbors for each locality[11]. Figure A.17, in the Appendix, is an example of the k-nearest neighbor's definition with *k* equal to three. One can see in this illustration that there is one centroid associated with each locality. For example, the county of interest (in green), has three places and four centroids, one extra for the non-place. The figure shows a two-way arrow, demarcated by a letter representing the line, and a table to the right of the figure containing the distance between the points. The distances in the table show that line segments A, B, and C represents the three shortest distances between any points ending in the county of interest. Since the non-place is the focal point of the diffusion, this nearest neighbors approach looks to be more efficient in identifying within county neighborhoods when compared to the "queen's matrix" because, on average, the places within the county will be the non-places only neighbors.

There will be some instances where there are less than three places, in these cases a place from neighboring non-place or the neighboring non-place itself will be included as a neighbor. This will lead to a few instances where between county diffusion may be identified. However, from the simple statistics above one can see that this will be the exception as opposed to the norm. For the purposes of maximizing the within-county connectivity and following the results of ancillary analyses, it seems that the $k = 3$ nearest neighbors approach is the most efficient definition.

Diffusion: Univariate versus Bivariate LISA Results

The primary point of departure in the literature builds on the early diffusion work of Cohen and Tita (1999). In this study, the authors introduced a creative use of available spatial statistics to identify potential patterns of diffusion. In their analysis they were able to identify patterns of contagious expansion, contagious relocation, hierarchical isolated increase, hierarchical isolated decrease, hierarchical global increase, and hierarchical global decrease (Cohen and Tita 1999). At the time, the spatially-centered approach used took advantage of the most cutting edge statistics available. The authors used the univariate LISA statistics at two points in time and interpreted the changes in classification as a type of spatial mobility, or diffusion, of crime.

Since that time there have been advances in the development of spatio-temporal measures, including the multivariate LISA statistic (see the model specifications section in Chapter XI). While the univariate approach taken by

Cohen and Tita (1999) pushed forward the analytic procedures involving spatio-temporal modeling, their procedure involved the use of differences in two static points in time for the LISA, simply involving temporal processes implicitly. The multivariate LISA, however, includes these two measurements at different time in a *single* statistic, therefore explicitly capturing space and time in a single statistical procedure, along with an associated significance test.

The univariate LISA statistic indicates the degree of linear association between the value of one variable at locality *i* and the average of another variable at neighboring locations (Anselin et al. 2002). However, when implementing the statistic with the *same* variable at different points in time (i.e. crime in 1990 and 2000), the statistic indicates the dynamic interplay of neighborhood relations and a pre-determined temporal lag (Anselin et al. 2002). Following one of the very few research projects to implement this procedure (Anselin and Sridharan 2000), these results are to be interpreted as contagion if positive spatial association is reported (High-High or Low-Low) and space-time outliers if negative spatial association is reported (High-Low or Low-High). Of importance in this dissertation project is the identification of contagious diffusion patterns from places to non-places.

In order to compare these empirical results against the earlier Cohen and Tita results, both the univariate and bivariate LISA results are reported in table

21. This will allow for a degree of "ground-truthing" in which the theoretical interpretations of the bivariate analyses can be checked against the 'known' univariate interpretations from the Cohen and Tita work. Since the larger dissertation is interested in the within-county redistribution of criminal offending from core places to periphery non-places, the values used in the LISA analysis are related to the proportion of the overall crime in the larger county accounted for by the i^{th} locality.

This change in the proportion of crime is important as if areas involved in the diffusion of high criminal offending from places to non-places were identified, one would expect the proportion of criminal offending that takes place in the non-places to have risen. However due to the unique relationships among each individual locality, it is possible that a High – High cluster may be associated with place to place diffusion, which is not the subject of the current project. Therefore, if a High – High cluster exists and a place is high in 1990 and the non-place gains in crime and is high in 2000 (via a shift in the within-county proportion of crime), there is evidence of potential contagious diffusion. On the same point, a Low – Low cluster that involves a non-place which decreases its proportion of crime over the time would be considered an area in which lower rates of crime existed in the places and spread outward in a diffusion pattern to the non-places.

Table 21. Crosstabulation of Univariate versus Bivariate LISA Classification of Type-Specific Crime for Each Locality, 1990 – 2000

Univariate Classification[1]	Bivariate Classification (Row Percentage)					
	Not Significant	High - High	Low - Low	Low - High	High - Low	Total
Total Crime						
Stationary	7369	351	270	187	246	8423
Contagious						
Expansion	3 (7%)	**26 (58%)**	**14 (31%)**	0	0	45
Relocation	0	0	0	0	0	0
Hierarchical						
Isolated Increase	0	0	0	0	0	0
Isolated Decrease	1 (7%)	2 (14%)	0	**11 (79%)**	0	14
Global Increase	0	0	0	0	0	0
Global Decrease	0	0	0	0	0	0
Column Total	7373	379	284	198	248	8482
Property Crime						
Stationary	7367	334	287	184	248	8420
Contagious						
Expansion	2 (4%)	**28 (61%)**	**15 (33%)**	1 (2%)	0	46
Relocation	0	0	0	0	0	0
Hierarchical						
Isolated Increase	0	0	0	0	0	0
Isolated Decrease	0	0	0	**16 (100%)**	0	16
Global Increase	0	0	0	0	0	0
Global Decrease	0	0	0	0	0	0
Column Total	7369	362	302	201	248	8482
Violent Crime						
Stationary	7250	450	273	174	262	8409
Contagious						
Expansion	5 (9%)	**24 (45%)**	**23 (43%)**	0	1 (2%)	53
Relocation	0	0	0	0	0	0
Hierarchical						
Isolated Increase	0	0	0	0	0	0
Isolated Decrease	2 (10%)	0	0	**18 (90%)**	0	20
Global Increase	0	0	0	0	0	0
Global Decrease	0	0	0	0	0	0
Column Total	7257	474	296	192	263	8482

[1]Univariate Classifications from Tita and Cohen 1999

The table is organized around three sub-sections, each representing a type-specific crime rate. Within each of the three sections there is a crosstabulation of Cohen and Tita's univariate method (rows) by the bivariate method (columns).

The results support the work of Anselin and Sridharan (2002), which suggests that positive spatial autocorrelation (High –High and Low – Low) is associated with contagious diffusion while negative spatial autocorrelation (High – Low and Low – High) is associated with spatial outliers or hierarchical diffusion. In all three tables, about ninety percent of the cases that were identified as having contagious diffusion, using Cohen and Tita's method, are in columns representing positive spatial autocorrelation. In relation to cases identified as hierarchical by the Cohen and Tita method, between eighty and one hundred percent are classified as negative spatial autocorrelation by the bivariate method. The combined results show that the bivariate LISA is a consistent predictor of spatial diffusion within the theoretical framework put forth by Cohen and Tita (1999). Furthermore, it seems to capture more of the space-time interaction with a higher proportion of cases being identified as being part of a statistically significant cluster of spatial mobility involving reported criminal offending.

Geographic Distribution of Bivariate LISA Results

The results of the bivariate LISA procedures are reported in figures 34 – 36, representing the results for total, property, and violent crime respectively. Each of the figures uses the standard five-category color classification introduced by Anselin the Geoda software package (Anselin 2003), in which positive spatial clustering is identified by dark red (High – High) and dark blue (Low – Low). Negative spatial association is represented by purple (Low – High) and pink (High – Low). Furthermore and consistent with earlier maps, within each figure an inset of the Atlanta, GA area is included and the Global Moran's I coefficient is given along with it's associated p-value.

In figure 34 the bivariate LISA results are presented for the logged total crime rate in 1990 by the logged total crime rate in 2000. The most obvious results seem to be that the clustering of areas of high crime diffusion in the South, West, and along the coasts. Areas of low crime diffusion, in contrast, seem to be located in the interior of the country. The global Moran's I of 0.0997 at a p-value of less than 0.01 indicates that there does exist significant spatial association and that this association, on average, represents contagious diffusion. The inset of the Atlanta, GA area shows that the counties of Fulton, Clayton, and Fayette, to the West and South, all show signs of significant high place to non-place diffusion.

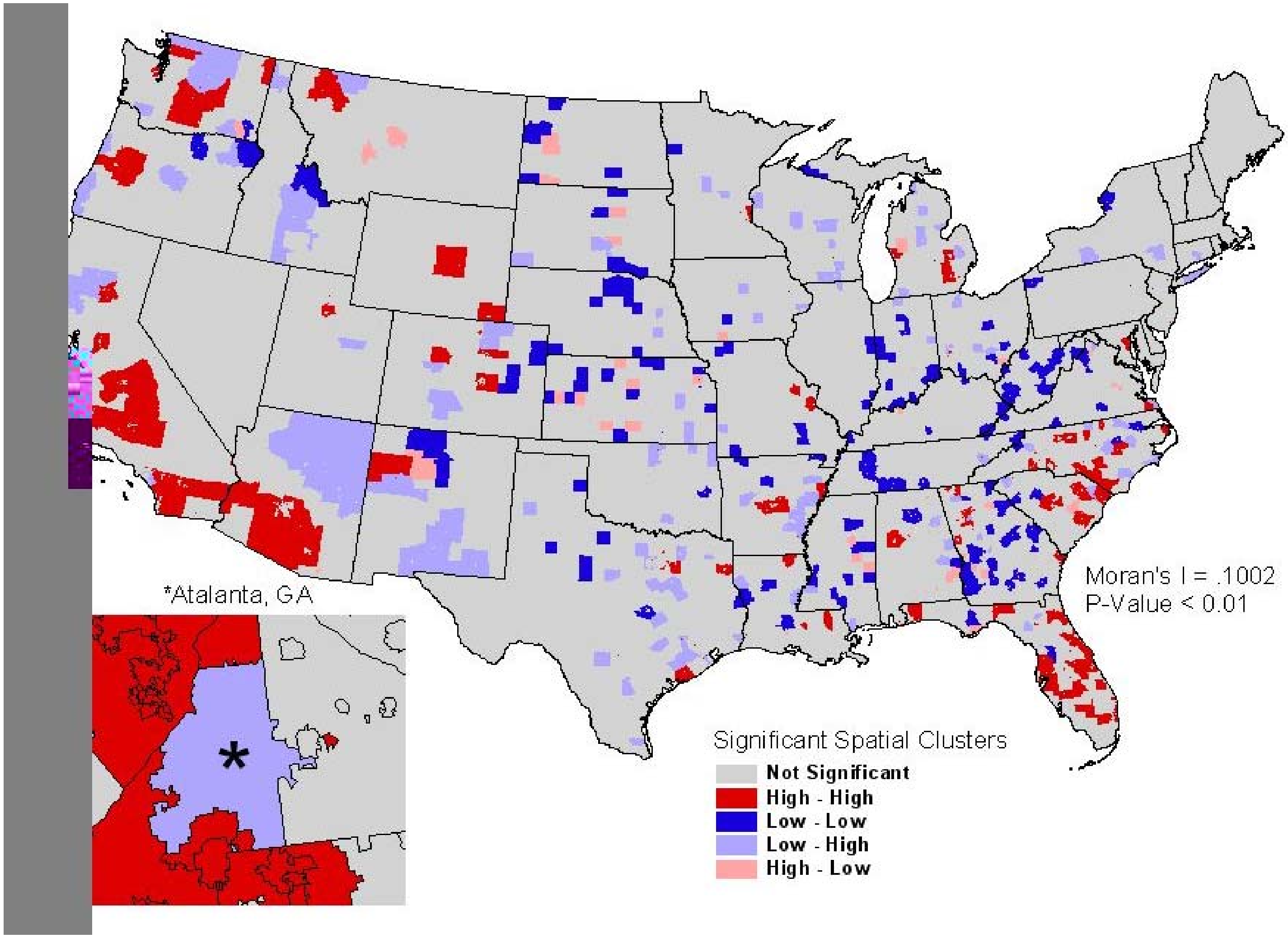


Figure 34. Bivariate LISA Results Showing Significant Spatial Clusters of Total Crime, 1990 – 2000

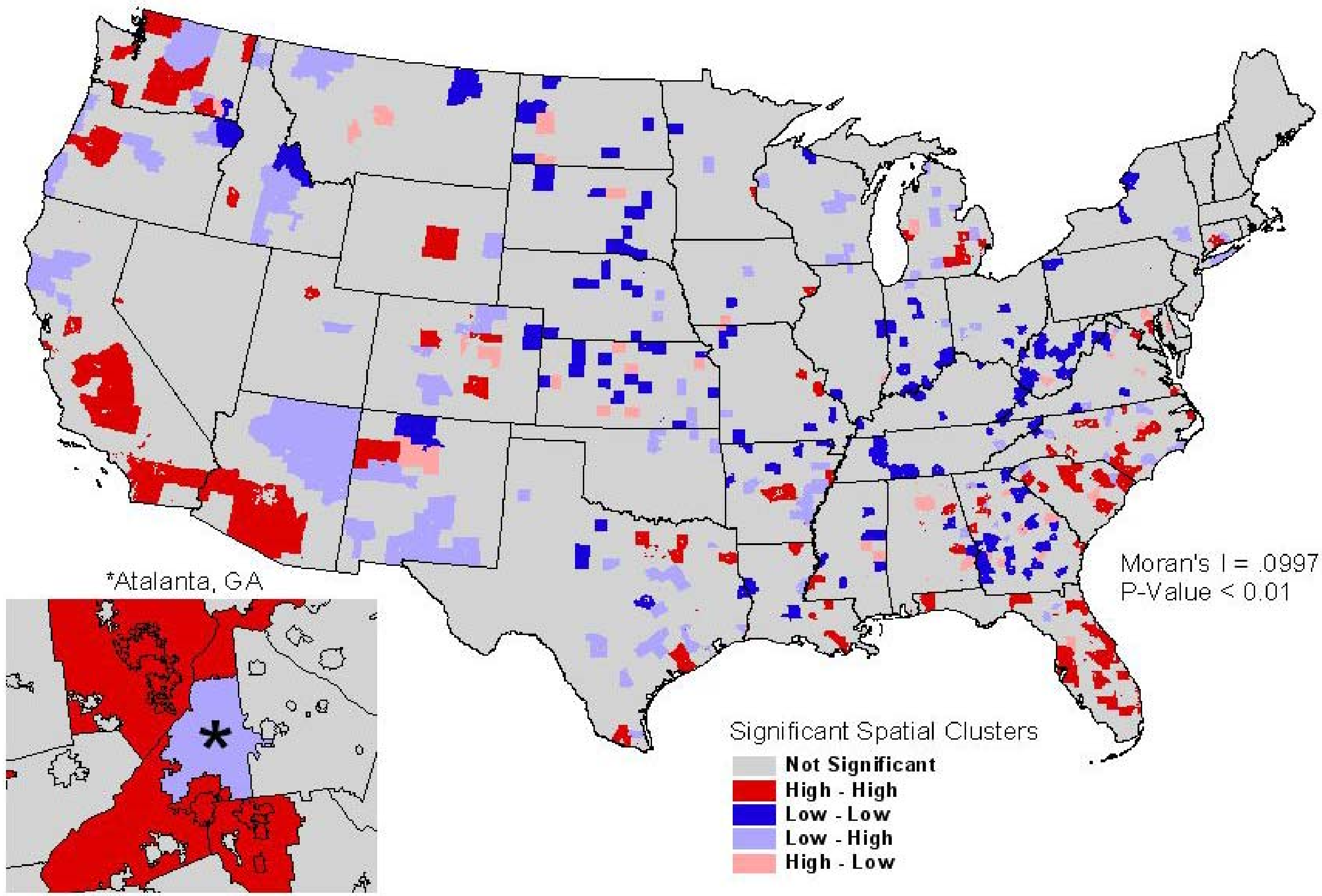


Figure 35. Bivariate LISA Results Showing Significant Spatial Clusters of Property Crime, 1990 – 2000

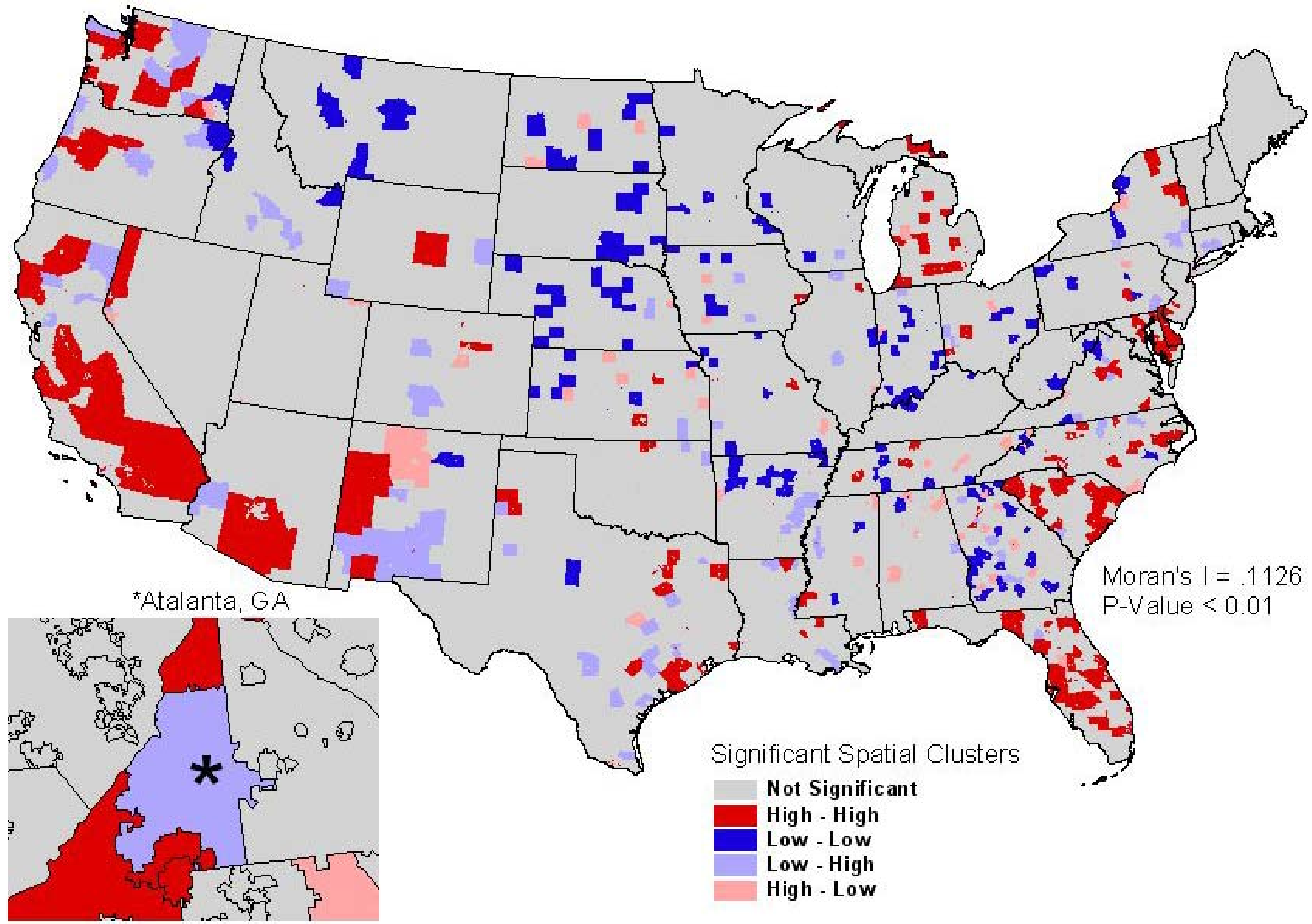


Figure 36. Bivariate LISA Results Showing Significant Spatial Clusters of Violent Crime, 1990 – 2000

Figure 35 and 36 report similar results for the logged property and violent crime rates, respectively. In both cases, there is significant evidence of positive spatial association, based on the global Moran's I coefficient. These patterns follow the same geographic patterns as those in figure 34 (total crime) by clustering primarily in the South, West, and along the coast. Within the inset of figure 35, the Atlanta, GA area contains basically an identical pattern concerning property crime, while only the results from Fulton County suggest diffusion of violent crime from places in 1990 to non-places in 2000.

In table 22 the type of diffusion by type-specific crime rate are broken down by metropolitan status and region. In relation to metropolitan status the table shows that, across the board, at least ninety percent of counties had no significant diffusion. However, there does seem to be a noticeable difference with metropolitan counties having a higher occurrence of significant diffusion compared to non-metropolitan counties. Within metropolitan counties there is a higher occurrence of high place to non-place diffusion of total crime and violent crime. On the other hand, there is not much difference in occurrence of high and low diffusion between places and non-places in regards to property crime. The findings reported in this table are very interesting in that they point to areas of higher levels of immigration, and population mobility in general, as being disproportionately more likely to have a significant cluster of diffusion (Brown

Table 22. Count and Percent of Counties by Type-Specific Crime Rate and Diffusion Trend, 1990 – 2000

Descriptives	Type Specific Crime By Diffusion Type (Type-Specific Row Percentages)								
	Total Crime			Property Crime			Violent Crime		
	Not Sig.	High	Low	Not Sig.	High	Low	Not Sig.	High	Low
Metropolitan Status									
Metropolitan	776 (90%)	54 (7%)	21 (3%)	782 (91%)	38 (5%)	31 (4%)	769 (90%)	71 (9%)	11 (1%)
Adjacent Non-Metropolitan	1161 (95%)	30 (2%)	33 (3%)	1161 (94%)	29 (3%)	34 (3%)	1143 (94%)	54 (4%)	27 (2%)
Non-Adjacent Non-Metropolitan	989 (96%)	12 (1%)	34 (3%)	990 (95%)	15 (2%)	30 (3%)	996 (96%)	20 (2%)	19 (2%)
Region									
Northeast	215 (98%)	2 (1%)	1 (0.5%)	216 (99%)	2 (1%)	0.00	206 (94%)	6 (3%)	6 (3%)
Midwest	1027 (97%)	14 (1%)	14 (1%)	133 (98%)	12 (1%)	10 (1%)	1017 (96%)	28 (3%)	10 (1%)
West	380 (92%)	16 (4%)	16 (4%)	381 (96%)	15 (6%)	16 (4%)	371 (90%)	31 (8%)	10 (2%)
South	1304 (92%)	64 (5%)	57 (4%)	1303 (91%)	53 (4%)	69 (5%)	1314 (92%)	80 (6%)	31(2%)

and Zuiches 1993; Frey 1987; Fey and Spear 1992; Fuguitt et al. 1988; Isserman 2001; Johnson et al. 2005; Lichter and Fuguitt 1982; Lichter et al. 1985; Wilkinson 1991).

In relation to differences by U.S. Census Region, most of the counties do not fall into either the 'high' or 'low' diffusion categories. However, there is noticeable difference in occurrences between the regions. The West and South both have higher levels of diffusion then do the Northeast and Midwest. Within the South, there is no real difference in occurrence of trend in diffusion for both total and property crimes, however high crime diffusion occurs at a meaningfully higher rate than low crime diffusion, concerning violent crime. Within the West region a similar pattern exists, with a six percentage point difference in violent crime occurrence. This is also important to note as it relates back to the earlier exploratory work, where high crime rates were found in these two areas, especially relating to violent crime.

Identifying Counties with Significant Contagious Diffusion

Because of the embedded nature of places within non-place territories, this dissertation project is mainly interested in the process of contagious diffusion. Therefore, only areas of positive spatial association will be examined further in an attempt to identify localities of high, and low, type-specific crime diffusion from places to non-places. The bivariate LISA procedure only identifies significant relationships among localities that are neighbors based on the nearest neighbors' definition. While this explicitly takes temporal relationships into account, it does not discriminate between place to non-place diffusion or vice-versa. Since this project is interested in identifying significant place to non-place contagious diffusion, the data were aggregated to the county level. If the bivariate cluster of the non-place was High –High and the non-place increased in crime, then the county is identified as having high place to non-place diffusion. Likewise, if the bivariate cluster of a non-place is Low – Low and the non-place decreased in crime, the county is identified as having low place to non-place diffusion.

Once these patterns are estimated to a national scale, there are ninety-six counties (about three percent) that were reported as having high total crime diffusion from place to non-place and eighty-eight (about two and a half percent) reported having low total crime diffusion from place to non-place over the time period. Eighty-two (about two and half percent) of the counties reported high property crime diffusion from place to non-place, while ninety-five (about three percent) reported low property crime diffusion from place to non-place over the time period.

The single largest group of counties that reported any single type of diffusion concerns the diffusion of high levels of violent crime. One hundred and forty-five counties (about five percent) report the diffusion of high violent crime from place to non-place and fifty-seven counties (about two percent) report the diffusion of low violent crime from place to non-place. The identified counties are listed in table A.11, in the Appendix, by state, type-specific crime rate, and trend in crime.

These results suggest that the spatial demography of type-specific reported crime differ to a good degree, especially when violent crimes are compared to either of the other two types. Also, it seems that over the period, where spatial mobility was present, it seemed to balance out between high and low crime diffusion, with only the diffusion of high violent crime being noticeably unbalanced. Perhaps, this is evidence of natural ebbs and flows concerning crime in places with the articulated non-places following suit, given a specified lag.

A few of the larger identified areas of diffusion include high place to non-place crime diffusion in San Diego, Miami, Atlanta, and Fairfax. In terms of low place to non-place crime diffusion, some of the notable areas include Fresno, Charlotte, and Salt Lake City. In figure 37 – 42, a closer look at some of these identified areas as a way of better understanding the outward movement of

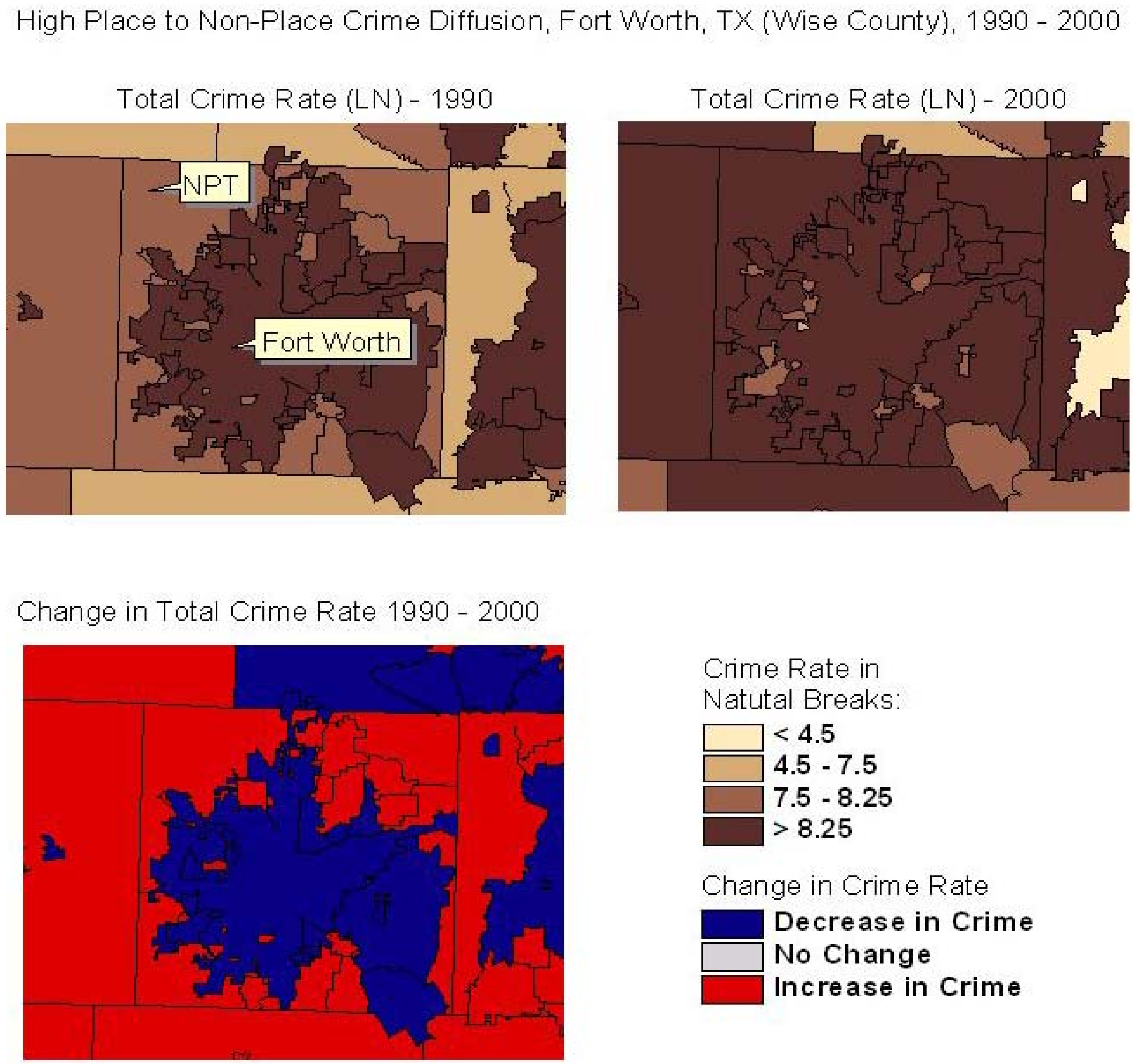


Figure 37. Selected Example of Place to Non-Place Diffusion of High Criminal Offending, Total Crime, 1990 – 2000

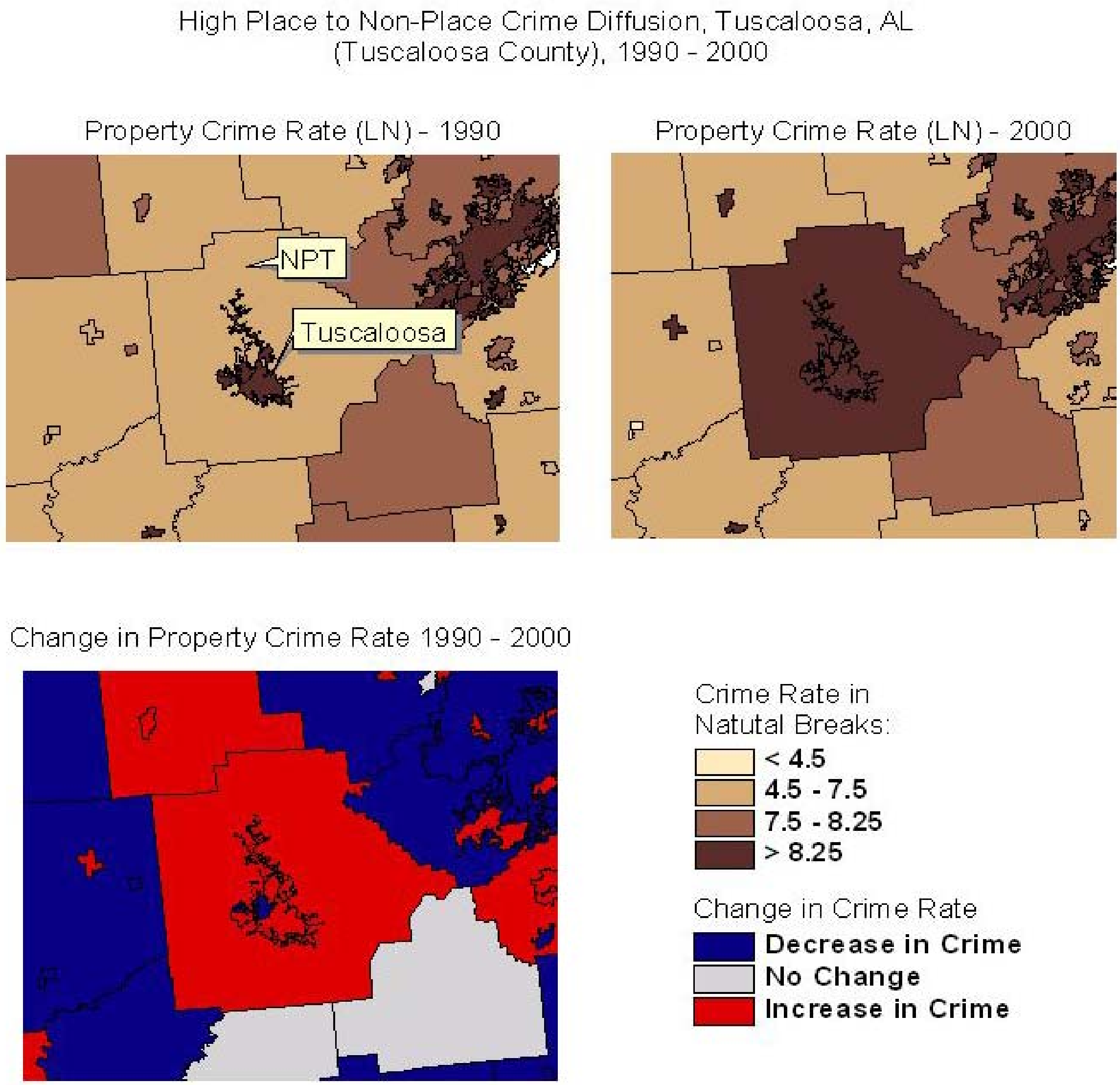


Figure 38. Selected Example of Place to Non-Place Diffusion of High Criminal Offending, Property Crime, 1990 – 2000

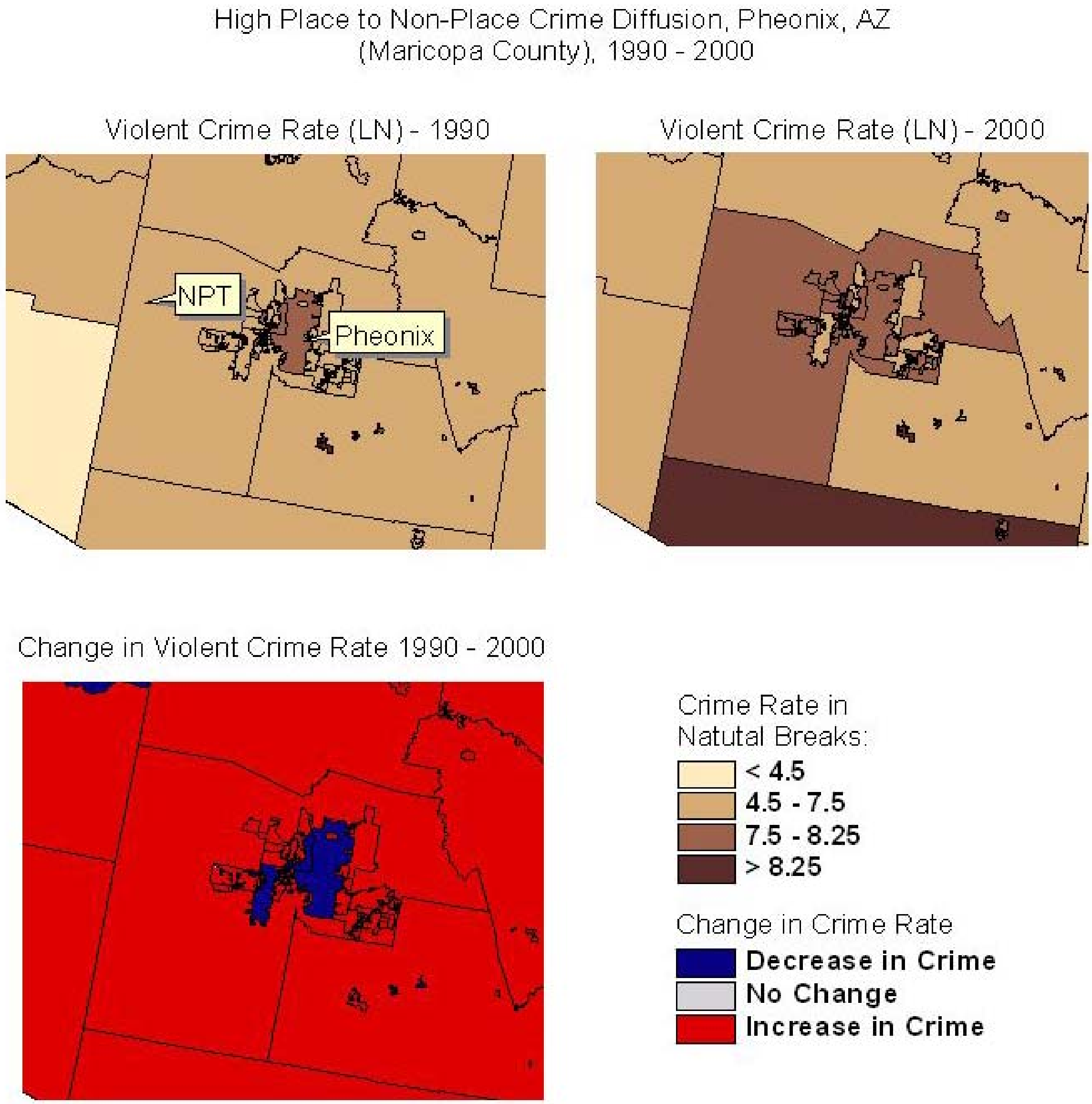


Figure 39. Selected Example of Place to Non-Place Diffusion of High Criminal Offending, Violent Crime, 1990 – 2000

crime behavior from places to non-places. The first three figures, 37 – 39, are concerned with the diffusion high type-specific criminal offending from 1990 – 2000. Conversely, figures 40 – 42 are focused in the diffusion of low type-specific criminal offending over the same time period.

Figure 37 focuses on the area of Fort Worth, TX (Tarrant). In the top two panels the logged total crime rate for 1990 and 2000 are set side by side, with the same standardized legend across all figures (using an average of the natural breaks method). The difference in the rates is also illustrated in the lower panel. In the Fort Worth area, one can see that in 1990 the crime rate was relatively higher in the place than non-places. However in 2000 the non-places have a similar high crime rate in comparison to the places. The difference mapped in the bottom panel shows that while the area of Fort Worth decreased, the non-place and many other surrounding non-places increased.

Next the area of Tuscaloosa, AL (Tuscaloosa County) is examined and shows an outward diffusion of high property crime rates from place to non-place. In this case, both the city of Tuscaloosa and the larger non-place both increased in the property crime rate while most of the surrounding areas decreased. The city of Phoenix, AZ (Maricopa County) shows significant high violent crime diffusion from place to non-place. In the change in violent crime panel at the bottom of the figure, the city of Phoenix decreased in violent crime

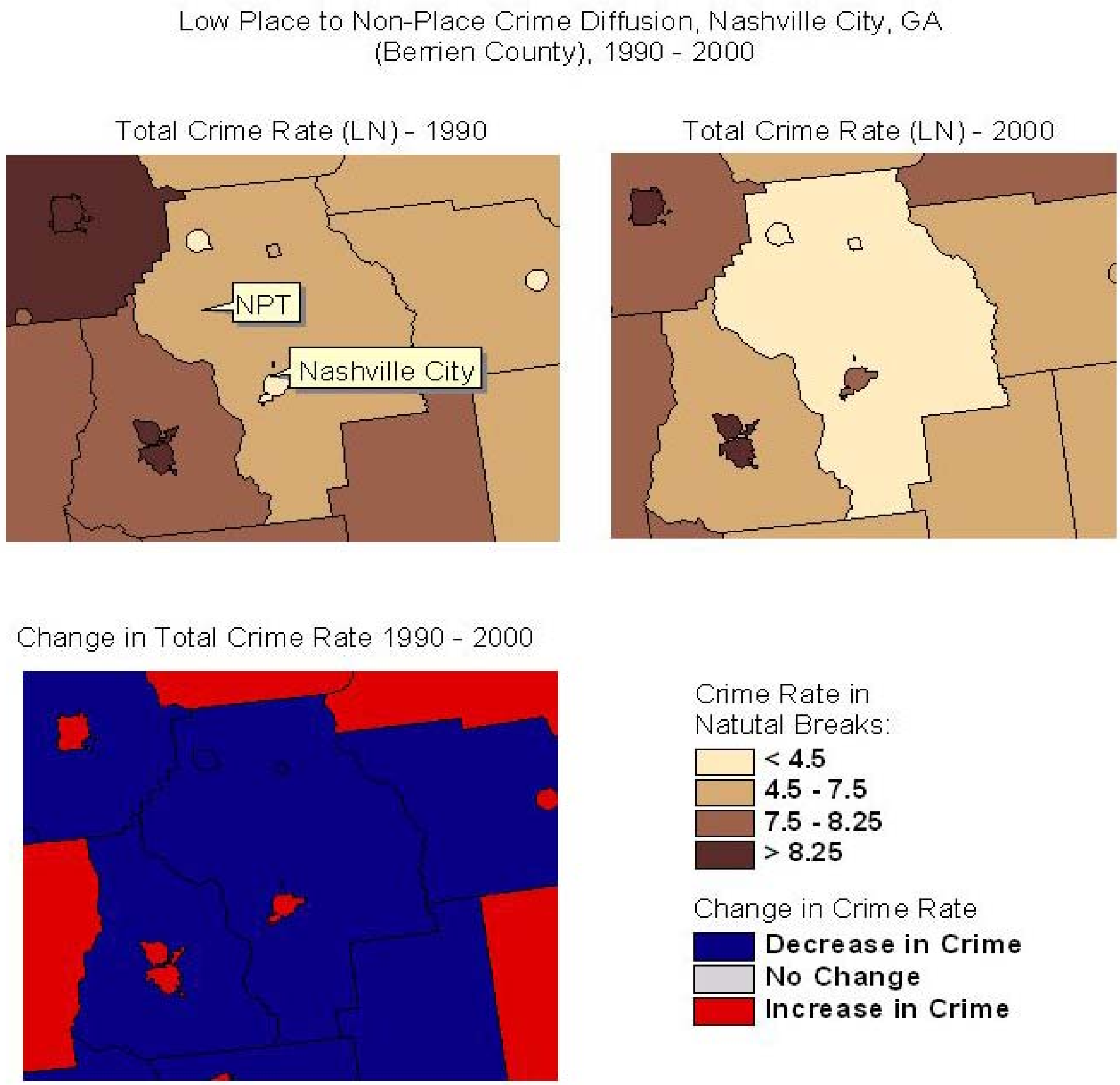


Figure 40. Selected Example of Place to Non-Place Diffusion of Low Criminal Offending, Total Crime, 1990 – 2000

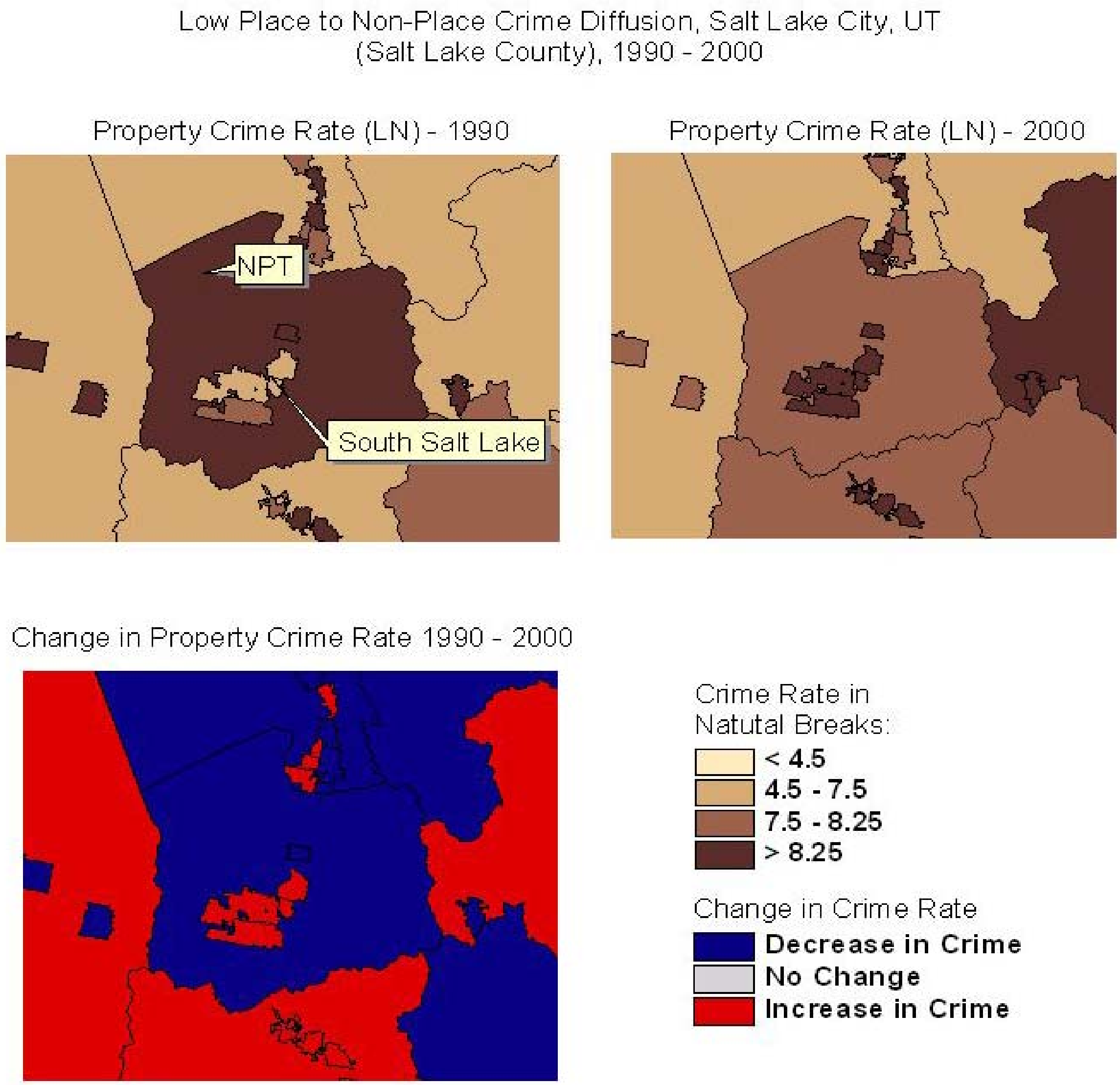


Figure 41. Selected Example of Place to Non-Place Diffusion of Low Criminal Offending, Property Crime, 1990 – 2000

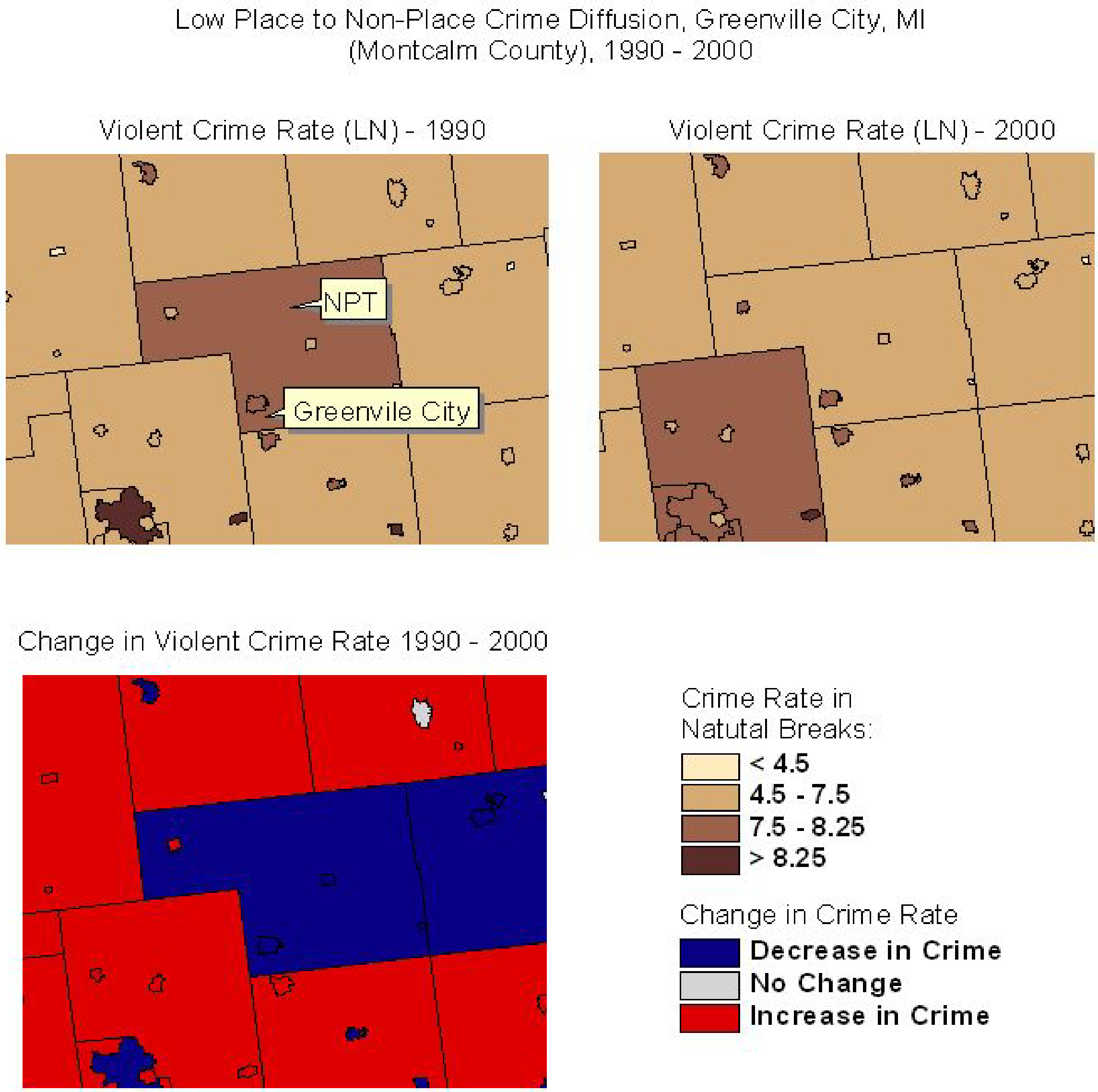


Figure 42. Selected Example of Place to Non-Place Diffusion of Low Criminal Offending, Violent Crime, 1990 – 2000

offending while the greater county of Maricopa increased along with what looks like a global increase in the entire area.

The next figures, 40 – 42, are concerned with the diffusion of low type-specific crime rates from places to non-places. In figure 40, Nashville City, GA (Berrien County) is an example of such diffusion in relation to the total crime rate. From the figure one can see that the greater county area decreased over the time period, following suit of the total crime rate in 1990 in the places inside of its borders. During the time period Nashville City, GA also increased in crime so this may be part of a larger cycle in which the crime ebb and flows with a slight lag associated with the non-place.

In figure 41, Salt Lake City, UT (Salt Lake County) is examined in relation to its change in property crime over the ten-year time period. From the figure it is evident that the lower property crime rates in the city in 1990 spread outward to the non-place territory in 2000. Figure 42 tells a similar story in relation to the violent crime rate in Greenville City, MI (Montcalm County). In 1990 the non-place territory had the highest crime rate in the area and in 2000 this reversed itself so that it had a much lower rate, similar to the places at the earlier point in time.

While these areas were carefully selected for presentation of the spatial mobility and diffusion phenomena, they tend to represent the fact that the West and South are over represented in terms of significant spatial clusters of diffusion. Furthermore, as is the subject of this dissertation all represent some form of contagious diffusion. Within the figures both *expansion* and *relocation* are evident, the former being the outward spread of the behavior while maintaining its level at the source and the latter representing the displacement or total movement of criminal behavior from one area to another. As an example, Phoenix, AZ illustrates almost and 'ideal type' of expansion as the higher crime rate in 1990 spreads to Maricopa County, while maintaining a high level at the source. In regards to relocation, Salt Lake City is a good example as the low crime rates in the places spread outward to Salt Lake County and were replaced with higher crime rates at the source.

Conclusions

A nearest neighbor approach to spatial neighborhoods was implemented in this chapter to identify within-county neighborhoods, with k=3 as the number of neighbors for each locality would have. Using this approach, each non-place has three neighbors, which is about the average number of places within counties in this analysis. Also, a bivariate LISA was used in order to identify patterns of contagious diffusion following the work of Cohen and Tita (1999). The neighborhood definition proved to work well as the bivariate results closely matched what was expected based on a replication and crosstabulation of Cohen and Tita's (1999) univariate use of the LISA for diffusion detection.

Geographically, all three type-specific crime rates proved to have significant clusters of diffusion, both locally and globally. Globally, the Moran's I suggest that there are non-random patterns of clustering at a national level and locally the locations of these non-random clusters were identified via the LISA statistics and associated significance tests. These clusters noticeably occurred in the South and West region, in comparisons to relatively lower numbers of occurrences in the Northeast and Midwest. Identified clusters of diffusion also occurred at a higher rate in metropolitan counties when compared to non-metropolitan counties. Within both region and metropolitan classifications, trends in type-specific diffusion (high or low) was not different, save the effects of violent crime, which disproportionately involved diffusion of high levels of offending from places to non-places.

Finally, this chapter identified a number of counties that reported some form of contagious diffusion from places to non-places. While these occurrences were somewhat randomly dispersed around the country, the process is identified in three hundred and sixteen counties across forty two-states. When "case-study" counties are examined across the differing diffusion trends and type-specific crime rates, the mapped rates at 1990 and 2000 closely resemble what would be expected based on what is currently known about diffusion. For instance, each of the figures directly illustrates some form of contagious diffusion, whether it is through the expansion of high violent crime in Phoenix, AZ or the relocation of low property crime in the Salt Lake City area. In fact, from 1990 to 2000 the spread of reported crime over the time period occurred in fashion consistent with movement from source, or origin, to the destination. This process of spatial mobility is consistent with the overall pattern of contagious diffusion.

CHAPTER VII

CONCLUSION

Summary of Findings

The primary purpose of this dissertation was to introduce a new approach to understanding rural and urban crime at sub-county geographies using existing Census place definitions. The resulting place-level geography has proven to be a useful tool as both an explanation of the causal determinants of reported criminal offending and in modeling the spatio-temporal interaction (or diffusion) of reported crime. Perhaps of equal importance is the point that the place-level geography may be phenomenologically more meaningful than the traditional rural and urban delineations (i.e. the census tract or the metro status of the county). In fact, the use of place versus non-place boundaries identified by the U.S. Census allows for the immediate understanding of whether one lives in an incorporated place or "out in the county". Using other sub-county geographies, such as tracts, is not as phenomenologically correct. For instance, it is expected that few individuals, save well trained applied demographers, could actually identify the Census tract they live in. On the contrary, most would immediately know whether they reside "in town" or "out in the country".

By quantifying the population and related characteristics by those who live in the city (place) and those who live in the "country" (non-place), this study has been able to test a number of locality-centered hypotheses about reported crime in contemporary America. These hypotheses have been specified to be two-fold. First, they are designed to test the usability of the new sub-county geography based on established theoretical perspectives. Secondly, they have been designed to identify patterns of spatio-temporal relationships of a more meaningful articulation between places and non-places. The former is interested in the application of multiple criminological perspectives to the explanation of a localities crime rate while the latter advances the current state of methodology aimed at understanding space and time interactions within the sub-field of the demographic examination of crime. Results provide important evidence of some success concerning both points.

In terms of testing the usability of the geography via a set of established theoretical perspectives, the results consistently show that the explanations of community-level type-specific crime rates can be reasonably accounted for using a spatial regression approach. While both the social disorganization and routine activities theoretical frameworks met expectations in their respective explanations of crime, it was the integrated ecological model that was most powerful. This is to be somewhat expected as in recent years the two perspectives have become more of a compliment and less competitive with one another (Smith et al. 2000; Miethe and Meier 1994).

On the second point, the implementation of the multivariate LISA statistic proved to be a very useful tool for identifying patterns of diffusion in the inter-decade mobility of reported crime. Upon initial inspection, the results very closely matched those of Cohen and Tita (1999), upon which they were built. The challenging part was defining and identifying a neighborhood that would maximize the within-county connectivity while minimizing any between-county connectivity of places and non-places. Ultimately, the k-nearest neighbors approach was chosen and a series of counties where significant diffusion of crime had occurred were identified, with a subset of those being presented as exemplars for further graphic illustration of the apparent diffusion process.

These results all directly inform the sets of hypotheses that were developed and formally stated at the end of Chapter II. The first set of hypotheses were associated with the statistical and spatial description reported type-specific criminal offending.

As proposed in hypothesis 1a, there is significant spatial clustering associated with the non-random distribution of all three type-specific crime rates at both points in time (1990 and 2000). While the differences were not substantial, the violent crime rate seems to concentrate more than the property or total rates, based on the slightly higher global Moran's I coefficient. This turned out to be a recurring theme as the violent crime rate consistently deviated from the other two types in many of the analyses. The major reason for this deviation is the much smaller proportion of the total crime rate defined as violent crime, thus as the total crime rate fluctuates it is driven most often by the property crime rate.

The second hypothesis (1b) in this first set dealt with the application of the place-level geography as a more optimal classifier for between-group ecological comparisons. The results illustrated that not only was this the case, but that the place-level geography was a better classifier than traditional categorical delineations of space, including U.S. Census region and metropolitan status. Furthermore, the place level geography proved to explain the highest amount of between-group classification while controlling for those other traditional classifiers and all possible interactions of them in a repeated measures ANOVA analysis. That is to say that, the place-level geography does a better job of maximizing the variations in reported crime between place type, when compared to traditional geographic classifiers such as the region of the country or metropolitan status.

The next set of hypotheses were concerned with the testing of established ecological theories of crime at the place versus non-place sub-county level of geography. From hypothesis 2a, it was proposed that the components of the social disorganization theoretical framework would explain criminal offending such that higher levels of urbanization, racial/ethnic heterogeneity, family disruption, and low level of socioeconomic standing would all produce higher rates of reported crime. The results show that, for the most part, these are also the patterns obtained at the sub-county level.

A few notable exceptions, however, include the effect of population size and the percent of housing female-headed. It was hypothesized from the literature review, that areas of higher population and a higher percent of the households female-headed would yield higher rates of reported crime. However, both consistently yielded lower, rather than the hypothesized higher, rates of crime. At least in the case of population size, the sheer size of the relative land area for non-places inflates their absolute population size when compared to many of the smaller places in the U.S. When using this place-level geography, it is apparent that the population density is a much better indicator of urbanization in these equations.

The next hypothesis in this second set (2b) proposed to test the same utility of the place-level geography through the implementation of the routine activities theoretical framework. The hypothesis stated that higher reported crime rates would be found in areas with more suitable targets, motivated offenders, and less capable guardians. The results show that is indeed the case with most of the variables predicting crime in the expected direction.

The most notable exceptions involving routine activities were the unexpected effects of population size, the rate of police officers deployed, and percent of female-headed households. Population size and the percent of female headed-households were identified in the social disorganization models. New to this discussion is the rate of police officers per one thousand residents. This rate consistently drove up the reported crime rate which, using a capable guardians perspective, is not as expected. However, it is possible that there is a lag involved with the introduction of more police to areas that have previously experienced higher crime rates. There is some support for this argument as the actual effect of the variable decreases over the ten-year period.

The final hypothesis in this second set (2c) took aim at testing the utility of the place-level geography in an integrated ecological model that combined the determinants from the two frameworks. The model proved to be the most efficient and powerful, while obtaining the expected effects of each determinant on the type-specific crime rate, net of all independent variables included in the model.

Across the three theoretical frameworks, determinants generally maintained consistently expected magnitudes and directions. The fact that these coefficients consistently affected crime in the expected fashion leads to the final conclusion that the place-level sub-county geography is a suitable unit of analysis for the ecological study of reported criminal offending. If the determinants would have yielded theoretically inconsistent results throughout the analysis, then it would suggest the lack of fit between this place-level geography and the examination of reported crime. However, since the determinants generally explained crime in the expected fashion, coupled with the relative superiority of the sub-county classifier compared to traditional county or tract classifiers reported in the previous literature, further suggests that the sub-county geography is a good addition to the ecological examination of reported crime.

The final hypothesis (3a) was concerned with the space-time interaction of reported crime at this level of geography. Primarily, the thesis was that there would be identifiable patterns of place to non-place contagious diffusion (Anselin and Sridharan 2000). Furthermore, these patterns were hypothesized to be non-random in the form of positive spatial clustering using a specific operationalization of the spatial neighborhood. These patterns were validated using a crosstabulation with a known alternative method of diffusion identification (Cohen and Tita 1999). The results made use of the multivariate (bivariate) LISA statistic (Anselin 1995), in which significant contagious diffusion was identified in three hundred and sixteen counties (or about ten percent) across all three type-specific crime rates.

These results are illustrated in figure 43 and are organized in three separate maps of the U.S. Each individual map represents a type-specific crime rate with the counties that were identified as having high crime diffusion from places to non-places being in red and the counties identified as having low crime diffusion in blue. The figures seem to show that the majority of the high crime diffusion occurred in relation to violent crime and primarily in the West and South Census regions.

The identification of the within-county neighborhood using the k-nearest neighbors approach with k=3, allowed for the maximization of within-county neighborhoods at the national scale. This approach also minimized the cross-county connectivity so that only significant within-county diffusion would be identified. This neighborhood definition coupled with the place-level geography provided a set of results in which the diffusion, from place to non-place, of high and low type-specific crime behavior was able to be confidently identified. While high crime diffusion was anticipated, the serendipitous finding of

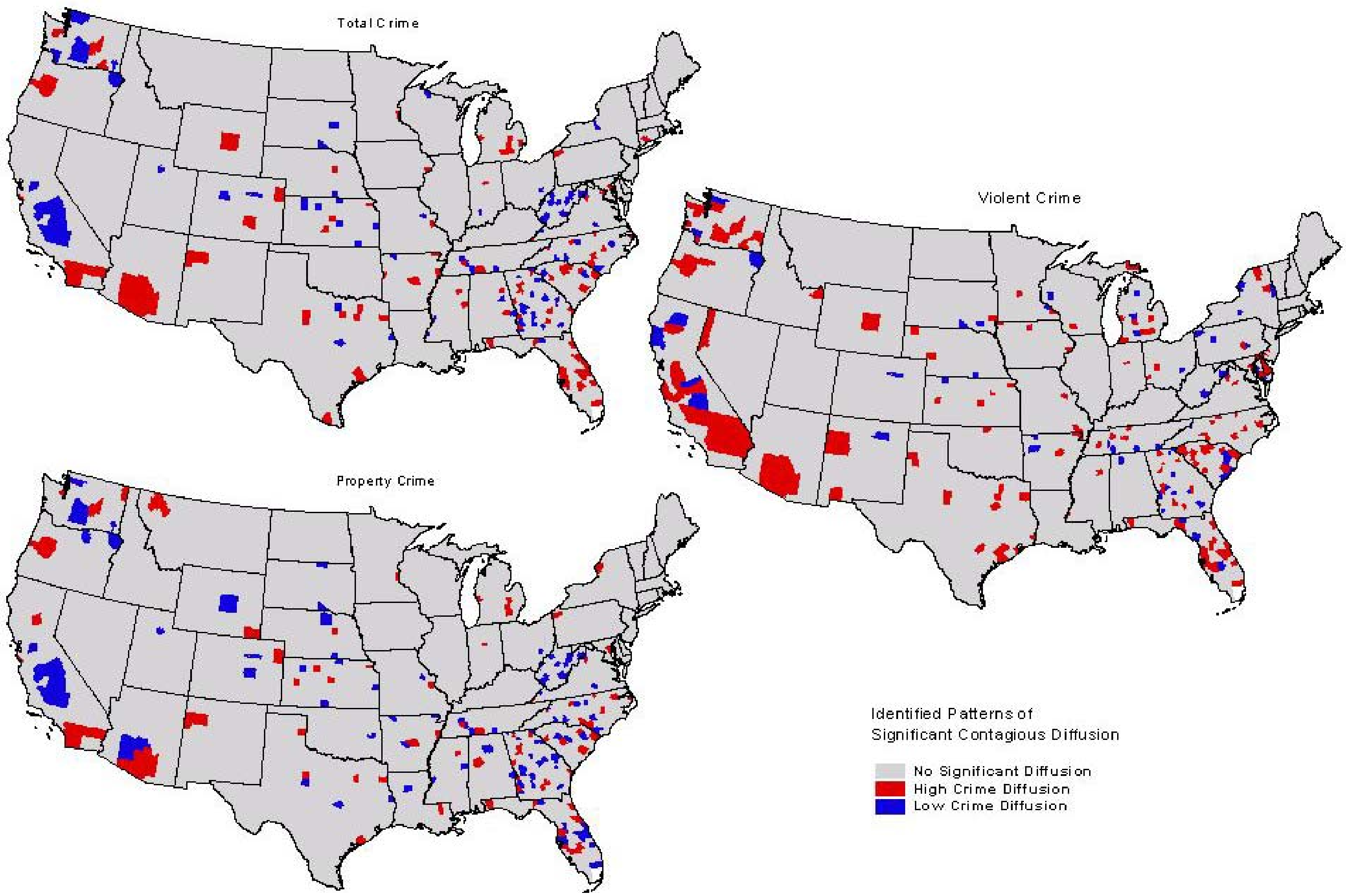


Figure 43. U.S. Counties by Identified Patterns of Contagious Diffusion, 1990 – 2000

significant diffusion of low crime was very intriguing. This finding begs for future study.

Discussion

This dissertation has shown that most (60 percent) of the variance in reported U.S. criminal offending is at the sub-county level. This simple but compelling result induces demographers of crime consider appropriate and meaningful sub-county geographers. In Chapter IV the results reported that only about forty percent of the variation could be accounted for using a county as the unit of analysis. These results were also consistent across all three type-specific rates of crime and points in time a decade apart. This suggests that the county-level was not the most optimal unit of analysis for such an examination of the determinants of crime reported to policing agencies. Ultimately, this highlights the importance of the continued development of sub-county analyses of criminal offending.

Furthermore, when the crime rates of localities are categorized by the metropolitan status of the larger county, it becomes more evident that examination of crime at the county-level is less than optimal[12]. These ancillary analyses showed that the least amount of between county variations could be explained by the county classifier in metropolitan counties, dropping from the population average of near forty percent to a sub-group low of thirty-three percent. Next, in a hierarchical fashion, the localities in the adjacent non-metropolitan category were able to explain about thirty-nine percent of criminal offending and those in the non-adjacent non-metropolitan category were able to explain about forty-nine percent of the variation. The low between county variance explained means that places and non-places within metropolitan counties are more heterogeneous while those within non-metropolitan counties tend to be more alike, with those in non-adjacent counties being the most homogeneous.

Theoretically, when thinking about the qualitative differences in the spatial ecology of metropolitan and non-metropolitan counties, one can begin to understand these disparities. First, metropolitan counties tend to have a larger number of places within their boundaries. For instance, recalling figure 1, where the place-level geography is first introduced, in the non-metropolitan Golden Triangle Region, the counties have a small number of identified places within their borders. However, in each of the type-specific crime rate maps (in figures 9-20 and 28-36), an inset of the metropolitan Atlanta, GA area was included. In each of the surrounding counties, multiple places could be identified within the county borders. The sheer larger quantity of place localities in metro areas increases the likelihood of having counties that are more heterogeneous than non-metropolitan counties.

Secondly, in places within metropolitan counties, population tends to concentrate in a much higher degree than in places within non-metropolitan counties, meaning that places in metropolitan counties are much more likely to differ from their paired non-place territory than those in non-metropolitan counties. For instance, in Louisville, KY, one can be in the city center of a metropolitan area with over a million people in the north of the county or thirty miles south, and in the same county, be in small unincorporated enclaves surrounded by forest. On the contrary, places in non-metropolitan counties, such as Starkville in Oktibbeha County, MS, may have a slightly different deportment related to criminal offending than the greater non-place territory. However, the degree of place versus non-place disparity is going to be much smaller than that of the aforementioned example in Louisville, KY.

The qualitative difference in contextual situation as based on the metropolitan classification of the larger county brings another important point to light. This concerns previous analyses that have fallen short in examining the ecological/neighborhood effects and determinants of reported criminal offending. These studies have fallen short for a couple of reasons. First, for the most part the examination of community-level crime has been performed at the county-level.

Second, where sub-county analyses have taken place, they have focused on a small area or group of areas in the nation, usually using census tracts within select metropolitan areas. However it has been shown here that the county is not the optimal unit for such studies. Therefore, while the previous work in this area has certainly given this study a sturdy foundation upon which to build, they have been less efficient than this dissertation hopes to be by examining reported crime at the sub-county level and at a national scale. The sub-county results will contribute to the field by introducing an ecologically meaningful unit of analysis, while the national-scale of the analysis contributes by examining all county types and not just limiting the analysis to a select few metropolitan counties.

Further validating the substantive usability of the sub-county geography is the successful explanation of community-level reported crime using two of the more dominant ecologically-centered theories of criminal offending, both of which have been tested numerous times at the county-level. However, at the sub-county level it is the integrated ecological approach that was most powerful in explaining criminal offending, as was hinted at by Smith et al. (2001). As an important side note, this suggested that the two theories are more complimentary than they are in opposition. Lastly, the implementation of this explanatory analysis at the place-level provided ample evidence of spatial processes related to criminal offending as in every model, across all type-specific crime rates and both years, showed significant spatial effects based on the significance of the neighborhood parameter variable.

It is also apparent that when dealing with the place-level geography, there are two observable spatial regimes[13] (Anselin 1988). The identification of these regimes was a hypothesized outcome of the place-level geography in which it is theorized that crime in places (more urban areas) will trend in a different fashion, whether by intensity or direction, than the crime in non-places (more rural areas). As documented, core places and periphery non-places are expected to exhibit fundamentally different 'behaviors' in terms of criminal offending (Agnew 1993; Lightfoot and Martinez 2003). In general, crime was identified as occurring at a higher rate in places, especially in the year 2000, and within all theoretical approaches there were significant place-level interactions among a select few determinants. These results suggest that space does matter in understanding ecologically-related explanations of reported crime, and at the sub-county level place-type also matters.

Based on some of the explanations put forth by the researchers such as William Julius Wilson (1987; 1991), a set of place-level interaction variables were tested in order to better understand the secondary effects of living in urban localities versus more rural localities on the existing effects a number of community-level socioeconomic determinants had on criminal offending. As hypothesized, living in female-headed households affected individuals within places more than it did individuals who resided in non-places, suggesting an inner-city, more urban culture of poverty, type of explanation. However, contrary to this line of theoretical thinking the effects of income per capita, percent with a college degree, and unemployment all consistently had a larger effect in non-places. In contrast to Wilson's thesis, this suggests rural deprivation approach centered on the increasing disparity gap between those in metropolitan America and those in the rural hinterlands (Tickamyer and Duncan 1990; Strait 2001; Knight and Song 1999). Based on this approach, there is more of a penalty to not be educated or not being employed in rural areas because of the fact that there are less public works programs and a lack of readily available transportation.

While each of the place-level interactions can be explained by several rural-urban disparity perspectives, the important point here is that there exists a significant differential by place-type that is interpretable. That is, some expected and substantively meaningful process is taking place at this sub-county level of geography. This successful examination of place-level reported crime using the social disorganization and routine activities theoretical frameworks adds merit to both the geography itself and the existence of two distinct spatial regimes in operation form, places and non-places.

This examination of reported crime also explored a new method for the examination of spatio-temporal processes related to the spread of criminal offending behavior. The primary interest of this dissertation was to marry such methods to the place-level geography in order to identify counties within the U.S where significant spatial mobility of crime could be identified through patterns of diffusion. The results suggest that there do exist such patterns and they are identifiable using the methods employed here. There also exists specific patterns associated with areas that were identified as counties in which significant diffusion of criminal behavior from places to non-places occurred during the time period of 1990 to 2000[14]. These processes occurred in adjacent non-metropolitan counties at higher rate than they did in metropolitan or non-adjacent non-metropolitan counties. They also occur more often in South as compared to all other regions.

Theoretically, it seems that this high level of spatial mobility in these areas may be linked to the high level of general population mobility. Meaning that, as population has deconcentrated from cities to suburbs and moved in a southward trend nationally, there may be a link between the diffusion of behavioral processes such as criminal offending and the diffusion of people through migration or even commuting. This brings to light another interesting connection concerning the substantive articulation of demography and crime. As individuals are the perpetrators of acts such as crime, it is generally plausible that the bulk of identifiable mobility in such processes will follow the trends of population mobility as outlined by more traditional demographic analyses. Therefore, one would expect to see the highest activity of crime diffusion in areas that have been empirically identified as having the highest activity of population mobility. This will be the focus of further study based upon these data.

Finally, this discussion must acknowledge that the continued development of theory concerning the demography of crime can be advanced through the sustained progress made toward identifying appropriate methods and ecological units of analysis. Recently, the work of Messner, Anselin, Baller, Cohen, Tita, and several others outlined in this project have helped to do just that. It is hoped that this dissertation might make a slight contribution in helping to push those methods and theory even further along.

Limitations

This dissertation suffers from a number of limitations that must be acknowledged in this section. First and foremost, when dealing with any temporal modeling concerning with diffusion, it is good practice to introduce a number of different time lags for sensitivity analyses (Anselin 1995). This project chose a static ten-year period in which to examine the diffusion of crime in 1990 to

2000. While this analysis did provide evidence of the spatial mobility of crime within counties through patterns of contagious diffusion, it may have missed other important temporal processes. For instance, perhaps the time lag on place to non-place diffusion is a smaller five year period or perhaps even a one year period. If that is in fact the case, then this dissertation simply uncovered time series related differences at T_1 and T_2, while not fully understanding the within-period variability that ultimately led to the identified net change.

The second limitation identified here is related to data used in the analysis. The UCR data is a tabulation of reported crime by theoretically every police agency in the U.S. One limitation to using the data is that only about ninety percent of total agencies actually report. While this is acceptable, it does leave out ten percent of all agencies. These agencies may or may not impact the final results, but it is important to not potential limitations to the use of the primary data source.

Next in regards to the use of UCR data is the fact that this dissertation is dealing with *reported* crime. It is well known that reported crime often undercounts the actual crime of an area and this undercount varies widely on the type of crime (Maltz 2003; 2006; Maltz and Targonski 2002). For instance, it has been documented that individuals that are raped are much less likely to report the offense the police, when compared to most any other type of crime

(Hindelang 1978). Furthermore, the UCR itself has a number of other documented problems including the fact that much of the data is imputed due to the fact that of the ninety percent of agencies that report, many do not report for the whole year (Maltz 2003; 2006; Maltz and Targonski 2002). Instead they may report for one month and then the data has to be imputed for the rest of the year via an algorithm that takes seasonality of crime and other determinants into effect (Maltz 2003; 2006; Maltz and Targonski 2002).

While there may be other smaller issues, overall this time lag sensitivity and data source problems are believed to be the most important. Net of these limitations, the time series identification of patterns of spatial mobility and contagious diffusion still proved to be meaningful. It is hoped that these results will help to push forward the analysis of space, time, and all types of demographic count data. In regards to the data issues, the UCR has long been documented as having a noted set of issues. However it has also been documented as being the best available data for a complete national scale tabulation of reported crimes (Wolfgang 1963; Maltz 2003; 2006).

Implications and Future Research

With the noted limitations, this dissertation makes a number of important contributions centered on moving the analysis of spatio-temporal processes forward and in the general area of ecological analyses. Methodologically, the use of the multivariate LISA as an identifier of spatial mobility has proven to successfully replicate earlier work using a univariate approach (Cohen and Tita 1999). Even more beneficial is the fact that this approach appears to be more sensitive to such mobility as it identified many more cases of significant non-random clustering than the previous univariate method. This allows for the ability to identify much more of the space time interaction while efficiently examining the two in a single procedure. Furthermore, this procedure has implication beyond the analysis of crime, particularly in the analysis of more traditional demographic count data such as population mobility.

Another important methodologically related implication of this dissertation is the introduction of the place-level classifier. Places have long been studied as units of analysis but such studies have neglected the large population that does not live in this Census-defined entity. The introduction of the place versus non-place geography allows for the examination of sub-county populations at a national scale (Howell et al. 2008). Ultimately, the place-level geography proved to be more statistically efficient and powerful as a geographic classifier of reported crime than many of the traditional sub-regional delineations.

The relative success of each of these tools has pushed forward the ecological examination of the demography of crime. There has long been an argument as to the optimal geographic resolution to analyze community level criminal offending (Baller et al. 2001; Hipp 2007; Messner and Anselin 2004; Messner et al. 2005). As noted throughout this project, the two primary components have been the county and the census tract. The county has often been deemed to be to large and heterogeneous, while the census tract too small, not inclusive of all neighborhood components, and lacks a phenomenology of individual undertaking. The introduction of the place-level geography, which fits neatly into a middle area, and the use of the multivariate LISA as an identifier of diffusion has built upon these well established lines of research in the field.

These implications, with the above mentioned limitations, lay the ground work for a potentially rich line of research. First, a sensitivity analysis should be under taken in order to better understand the appropriate time lag for within-decade examinations of the spatial mobility of reported crime. Since the UCR data are collected on an annual basis, this can be done. From this analysis, a template can be developed, from which a series of future analyses may sprout. A continued analysis of reported crime can be examined at almost a real-time pace, as the annual data can be processed and inserted into the current analysis on a yearly basis. Once the optimal time lag of spatial mobility is identified, this will allow for a continued understanding of how crime is moving across the geographic landscape.

In a more demographic vein, this template can be introduced to better understand population mobility itself. One focus could be in the continued concentration and deconcentration of the population to and from the inner-city. Currently, there is a lot of work on the gentrification of city centers and the associated population concentration that comes along with that. Likewise, many have examined the continued flight of the middle class form the city center to the outlying suburbs and rural areas (Brown and Zuiches 1993; Frey 1987; Fey and Spear 1992; Fuguitt et al. 1988; Isserman 2001; Johnson et al. 2005; Lichter and Fuguitt 1982; Lichter et al. 1985; Wilkinson 1991). The implementation of this method will allow for the identification of such diffusion patterns among localities within the counties. This can be extended even further to understand the other demographic components, such as race, associated with this mobility, including processes like white flight and immigration.

In conclusion, it turns out that the most powerful and efficient ecological unit for the examination of the reported crime rate is the place-level, which is inherently designed to differentiate between areas of population concentration and areas without. In hindsight, it makes perfect sense that when studying rural and urban differentials in crime, the place level has many optimal advantages.

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APPENDIX A

ANCILARY TABLES AND FIGURES

Table A.1. Mean Differences in Type-Specific Crime Rates Across U.S. Region, Metropolitan Status, Place-Level, and Temporal Period

	(LN) Total Crime		(LN) Property Crime		(LN) Violent Crime	
	1990	2000	1990	2000	1990	2000
Comparison Groups	Mean (F-Stat)	Mean (F-Stat)	Mean (F-Stat)	Mean (F-Stat)	Mean (F-Stat)	Mean (F-Stat)
Place Level Geography						
Place	8.31	8.32	8.08	8.02	6.61	6.88
Non-Place Territory (NPT)	7.33	7.30	7.12	7.01	5.64	6.17
F-Statistic	(1,228.592***)	(1,138.652***)	(1,249.205***)	(1,263.052***)	(971.357***)	(488.841***)
Eta-Square	0.127	0.128	0.103	0.118	0.130	0.050
Metropolitan Status^						
Metropolitan	8.24	8.23	8.01	7.94	6.51	6.83
Adjacent Non-Metropolitan	7.79	7.79	7.56	7.48	6.12	6.51
Non-Adjacent Non-Metropolitan	7.58	7.60	7.36	7.28	5.91	6.35
F-Statistic	(195.577***)	(151.687***)	(201.482***)	(184.617***)	(121.501***)	(78.809***)
Eta-Square	0.044	0.046	0.029	0.035	0.042	0.019
U.S. Region~						
Northeast	7.92	7.69	7.69	7.38	6.16	6.23
Midwest	7.79	7.67	7.59	7.44	6.04	6.31
West	8.31	8.32	8.07	8.02	6.71	6.96
South	7.92	8.07	7.69	7.72	6.24	6.82
F-Statistic	(48.031***)	(84.080***)	(43.121***)	(75.746***)	(64.398***)	(112.823***)
Eta-Square	0.017	0.015	0.022	0.029	0.026	0.038
Temporal Period						
1990	7.95		7.73		6.25	
2000	7.94		7.64		6.62	
F-Statistic	(0.01 [NS])		(16.131***)		(265.746***)	
Eta-Square	0.000		0.001		0.015	

*** Mean difference is significant at < .001 level

^ All possible combinations are significantly different from one another at < .001 level.

~ Northeast and South were not significantly different in terms of total crime rate and property crime rate in 1990 and the Northeast and the Midwest were not significnatly different in all type-specific crime rates in 2000. All other possible combinations were significant at < .001 level.

Table A.2. OLS Regression Results of Logged Total Crime Rates on a Social Disorganization Theoretical Framework

	Individual Component Models - Social Diorganization Theory^								Fully Integrated SD Model		Place Indicator Interactions	
	Model SD1		ModelSD2		Model SD3		Model SD4		Model SD5		Model SD6	
Independent Variables	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Popualtion Size	-0.123***	-0.228***	--	--	--	--	--	--	-0.143***	-0.235***	-0.185***	-0.267***
Popualtion Density	0.226***	0.207***	--	--	--	--	--	--	0.223***	0.184***	0.242***	0.180***
Percent Black	--	--	0.005***	0.010***	--	--	--	--	0.003*	0.007***	0.006*	0.012***
Resedential Segregation	--	--	-0.510***	-0.923***	--	--	--	--	0.142**	0.154**	0.155**	0.227***
Income per Capita	--	--	--	--	0.384***	-0.432***	--	--	-0.020	-0.141	0.959***	0.717***
Percent College Degree	--	--	--	--	0.051***	0.136**	--	--	0.042***	0.028	0.040	0.092**
Percent Unemployed	--	--	--	--	0.185***	0.101***	--	--	0.063***	0.025*	0.161***	0.053*
Percent Female-Head HH	--	--	--	--	--	--	0.032***	0.046***	-0.001	0.000	-0.019*	-0.008
Percent Divorced	--	--	--	--	--	--	0.133***	0.323***	0.069***	0.277***	0.063***	0.259***
Percent Housing Own-Occ	--	--	--	--	--	--	0.010***	-0.016***	-0.009***	-0.012***	-0.010***	-0.013***
Place-Level Interactions												
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	--	--	10.387***	10.225***
x Percent Black	--	--	--	--	--	--	--	--	--	--	-0.002	-0.005
x Percent Female-Headed	--	--	--	--	--	--	--	--	--	--	0.022*	0.010
x Per Capita Income	--	--	--	--	--	--	--	--	--	--	-1.026***	-1.029***
x Percent College Degree	--	--	--	--	--	--	--	--	--	--	0.006	-0.063
x Percent Unemployed	--	--	--	--	--	--	--	--	--	--	-0.115***	-0.034
Constant	7.750***	8.800***	8.128***	8.263***	3.604	11.417***	6.181***	7.552***	7.683***	10.038***	-1.057	1.838
R-Square	0.174	0.159	0.017	0.045	0.030	0.024	0.107	0.090	0.210	0.200	0.222	0.211

*** P-value < .001; ** P-value < .01; * P-value < .05

^ SD1 - Urbanization, SD2 - Racial Heterogeneity, SD3 - Socioeconomic Status, SD4 - Family Disruption

Table A.3. OLS Regression Results of Logged Property Crime Rates on a Social Disorganization Theoretical Framework

	Individual Component Models - Social Diorganization Theory^								Fully Integrated SD Model		Place Indicator Interactions	
	Model SD1		ModelSD2		Model SD3		Model SD4		Model SD5		Model SD6	
Independent Variables	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Popualtion Size	-0.125***	-0.227***	--	--	--	--	--	--	-0.142***	-0.213***	-0.183***	-0.240***
Popualtion Density	0.223***	0.209***	--	--	--	--	--	--	0.223***	0.186***	0.242***	0.177***
Percent Black	--	--	0.004***	0.008***	--	--	--	--	0.002	0.006***	0.004	0.009***
Resedential Segregation	--	--	-0.511***	-0.872***	--	--	--	--	0.141**	0.148*	0.155**	0.213***
Income per Capita	--	--	--	--	0.396***	-0.377***	--	--	-0.080	-0.120	0.889***	0.722***
Percent College Degree	--	--	--	--	0.061***	0.153***	--	--	0.051***	0.046**	0.055*	0.100**
Percent Unemployed	--	--	--	--	0.165***	0.098***	--	--	0.048***	0.023**	0.135***	0.035
Percent Female-Head HH	--	--	--	--	--	--	0.029***	0.041***	-0.001	-0.002	-0.016*	-0.002
Percent Divorced	--	--	--	--	--	--	0.132***	0.305***	0.066***	0.252***	0.061***	0.234***
Percent Housing Own-Occ	--	--	--	--	--	--	0.010***	-0.016***	-0.009***	-0.012***	-0.010***	-0.013***
Place-Level Interactions												
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	--	--	9.544***	10.000***
x Percent Black	--	--	--	--	--	--	--	--	--	--	-0.002	-0.003
x Percent Female-Headed	--	--	--	--	--	--	--	--	--	--	0.017*	0.002
x Per Capita Income	--	--	--	--	--	--	--	--	--	--	-1.030***	-1.007***
x Percent College Degree	--	--	--	--	--	--	--	--	--	--	-0.003	-0.052
x Percent Unemployed	--	--	--	--	--	--	--	--	--	--	-0.103***	-0.528
Constant	7.556***	8.297***	7.917***	7.951***	3.287***	10.521***	6.009***	7.335***	7.401***	9.378***	-0.641	1.338
R-Square	0.176	0.170	0.016	0.042	0.029	0.026	0.100	0.090	0.208	0.209	0.218	0.220

*** P-value < .001; ** P-value < .01; * P-value < .05

^ SD1 - Urbanization, SD2 - Racial Heterogeneity, SD3 - Socioeconomic Status, SD4 - Family Disruption

Table A.4. OLS Regression Results of Logged Violent Crime Rates on a Social Disorganization Theoretical Framework

	Individual Component Models - Social Diorganization Theory^								Fully Integrated SD Model		Place Indicator Interactions	
	Model SD1		ModelSD2		Model SD3		Model SD4		Model SD5		Model SD6	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables												
Popualtion Size	-0.087***	-0.1517***	--	--	--	--	--	--	-0.096***	-0.143***	-0.143***	-0.211***
Popualtion Density	0.237***	0.162***	--	--	--	--	--	--	0.225***	0.142***	0.246***	0.172***
Percent Black	--	--	0.013***	0.013***	--	--	--	--	0.006***	0.008***	0.009**	0.010**
Resedential Segregation	--	--	-0.473***	-0.678***	--	--	--	--	0.065	0.085**	0.098	0.151*
Income per Capita	--	--	--	--	0.255***	-0.568***	--	--	-0.227**	-0.393***	0.895***	0.606***
Percent College Degree	--	--	--	--	0.017***	0.047**	--	--	0.023	-.017	0.097***	0.111**
Percent Unemployed	--	--	--	--	0.257***	0.102***	--	--	0.106***	0.027**	0.220***	0.089***
Percent Female-Head HH	--	--	--	--	--	--	0.049***	0.055***	0.003	0.004	-0.012	-0.005
Percent Divorced	--	--	--	--	--	--	0.143***	0.412***	0.093***	0.407***	0.085***	0.386***
Percent Housing Own-Occ	--	--	--	--	--	--	0.007***	-0.014***	-0.008***	-0.009***	-0.009***	-0.010***
Place-Level Interactions												
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	--	--	12.166***	11.966***
x Percent Black	--	--	--	--	--	--	--	--	--	--	-0.001	-0.001
x Percent Female-Headed	--	--	--	--	--	--	--	--	--	--	0.017	0.000
x Per Capita Income	--	--	--	--	--	--	--	--	--	--	-1.265***	-1.189***
x Percent College Degree	--	--	--	--	--	--	--	--	--	--	-0.095**	-0.140***
x Percent Unemployed	--	--	--	--	--	--	--	--	--	--	-0.133***	-0.074***
Constant	5.661***	7.038***	6.354***	6.794***	3.038***	11.723***	4.285***	5.744***	7.219***	10.185***	-3.177*	0.577
R-Square	0.143	0.084	0.026	0.039	0.043	0.032	0.136	0.101	0.207	0.150	0.223	0.169

*** P-value < .001; ** P-value < .01; * P-value < .05

^ SD1 - Urbanization, SD2 - Racial Heterogeneity, SD3 - Socioeconomic Status, SD4 - Family Disruption

Table A.5. OLS Regression Results of Logged Total Crime Rates on a Routine Activities Theoretical Framework

	Individual Component Models - Routine Activites Theory^						Fully Integrated RA Model		Place Indicator Interactions	
	Model RA1		ModelRA2		Model RA3		Model RA4		Model RA5	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables										
Income per Capita	-0.065	-0.611***	--	--	--	--	-0.238*	-0.288***	0.124	0.027
Percent College Degree	0.049***	0.141***	--	--	--	--	0.046***	0.050***	0.063**	0.186***
Percent Housing pre-1940	-0.005***	-0.010***	--	--	--	--	-0.009***	-0.016***	-0.010***	-0.016***
Percent Black	--	--	-0.015***	-0.005***	--	--	-0.008***	0.002	0.000	0.008***
Percent Below Poverty	--	--	-0.022***	-0.006*	--	--	-0.005*	0.004	-0.001	0.009**
Percent Female-Head HH	--	--	0.076***	0.080***	--	--	0.019***	0.007	-0.030***	-0.032**
Percent Unemployed	--	--	0.053***	0.025*	--	--	0.074***	0.031**	0.147***	0.068**
Percent Under 18	--	--	-0.007*	-0.016***	--	--	0.007*	-0.002	0.009**	-0.002
Percent b/w 18-24	--	--	0.010***	0.013***	--	--	0.002	0.003	0.004	0.004
Total Popualtion	--	--	--	--	-0.025*	-0.210***	-0.048***	-0.242***	-0.106***	-0.270***
Popualtion Density	--	--	--	--	0.165***	0.205***	0.160***	0.205***	0.244***	0.222***
Officers per 1k Pop	--	--	--	--	0.447***	0.154***	0.046***	0.120***	0.402***	0.109***
Place-Level Interactions										
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	2.045***	6.086***
x Percent Black	--	--	--	--	--	--	--	--	-0.009***	-0.007*
x Percent Female-Headed	--	--	--	--	--	--	--	--	0.056***	0.046***
x Per Capita Income	--	--	--	--	--	--	--	--	-0.301***	-0.611***
x Percent College Degree	--	--	--	--	--	--	--	--	-0.019*	-0.150***
x Percent Unemployed	--	--	--	--	--	--	--	--	-0.088	-0.049*
Constant	7.259***	13.627***	7.210***	7.448	6.900***	8.707***	8.865***	11.725***	5.952***	6.270***
R-Square	0.007	0.026	0.100	0.065	0.220	0.174	0.243	0.218	0.255	0.230

*** P-value < .001; ** P-value < .01; * P-value < .05

^ RA1 - Suitable Target, RA2 - Motivated Offender, RA3 - Lack of Capable Gaurdian

Table A.6. OLS Regression Results of Logged Property Crime Rates on a Routine Activities Theoretical Framework

	Individual Component Models - Routine Activites Theory^						Fully Integrated RA Model		Place Indicator Interactions	
	Model RA1		ModelRA2		Model RA3		Model RA4		Model RA5	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables										
Income per Capita	-0.104*	-0.552***	--	--	--	--	-0.225**	-0.290***	0.034	0.223
Percent College Degree	0.061***	0.159***	--	--	--	--	0.054***	0.071***	0.080***	0.197***
Percent Housing pre-1940	-0.005***	-0.010***	--	--	--	--	-0.009***	-0.015***	-0.010***	-0.016***
Percent Black	--	--	-0.015***	-0.005***	--	--	-0.009***	0.002	-0.001	0.005*
Percent Below Poverty	--	--	-0.022***	-0.010***	--	--	-0.005	0.002	-0.001	0.006*
Percent Female-Head HH	--	--	0.074***	0.079***	--	--	0.017***	0.006	-0.027***	-0.026**
Percent Unemployed	--	--	0.035*	0.022*	--	--	0.058***	0.029**	0.120***	0.051*
Percent Under 18	--	--	-0.009*	-0.015***	--	--	0.006	0.000	0.008**	0.000
Percent b/w 18-24	--	--	0.011***	0.015***	--	--	0.003	0.005	0.004	0.006*
Total Popualtion	--	--	--	--	-0.026**	-0.189***	-0.049***	-0.221***	-0.105***	-0.245***
Popualtion Density	--	--	--	--	0.162***	0.207***	0.159***	0.205***	0.244***	0.217***
Officers per 1k Pop	--	--	--	--	0.446***	0.158***	0.404***	0.125***	0.404***	0.116***
Place-Level Interactions										
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	1.043	5.660***
x Percent Black	--	--	--	--	--	--	--	--	-0.009**	-0.004
x Percent Female-Headed	--	--	--	--	--	--	--	--	0.052***	0.038***
x Per Capita Income	--	--	--	--	--	--	--	--	-0.189***	-0.567***
x Percent College Degree	--	--	--	--	--	--	--	--	-0.031	-0.139***
x Percent Unemployed	--	--	--	--	--	--	--	--	-0.074**	-0.031
Constant	6.626***	12.679***	7.110***	7.174***	6.707***	8.202***	8.611***	11.157***	6.595***	6.099***
R-Square	0.010	0.028	0.095	0.066	0.223	0.187	0.244	0.231	0.254	0.242

*** P-value < .001; ** P-value < .01; * P-value < .05

^ RA1 - Suitable Target, RA2 - Motivated Offender, RA3 - Lack of Capable Gaurdian

Table A.7. OLS Regression Results of Logged Violent Crime Rates on a Routine Activities Theoretical Framework

	Individual Component Models - Routine Activites Theory^						Fully Integrated RA Model		Place Indicator Interactions	
	Model RA1		ModelRA2		Model RA3		Model RA4		Model RA5	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Independent Variables										
Income per Capita	-0.167*	-0.750***	--	--	--	--	-0.456***	-0.452***	0.097	0.374*
Percent College Degree	0.006	0.053***	--	--	--	--	0.023	-0.014	0.108***	0.170***
Percent Housing pre-1940	-0.005***	-0.012	--	--	--	--	-0.007***	-0.015***	-0.008***	-0.015***
Percent Black	--	--	-0.013***	-0.003*	--	--	-0.005***	0.003*	0.003	0.005
Percent Below Poverty	--	--	-0.021***	0.007*	--	--	-0.006*	0.007*	0.000	0.013***
Percent Female-Head HH	--	--	0.086***	0.072***	--	--	0.024***	0.013*	-0.022*	-0.014
Percent Unemployed	--	--	0.113***	0.035**	--	--	0.120***	0.034**	0.212***	0.104***
Percent Under 18	--	--	0.001	-0.007	--	--	0.011***	-0.004	0.012***	-0.004
Percent b/w 18-24	--	--	0.006	0.008*	--	--	-0.006*	-0.004	-0.004	-0.002
Total Popualtion	--	--	--	--	0.023*	-0.130***	0.014	-0.148***	-0.046**	-0.213***
Popualtion Density	--	--	--	--	0.169***	0.160***	0.167***	0.169***	0.247***	0.213***
Officers per 1k Pop	--	--	--	--	0.498***	0.179***	0.469***	0.144***	0.445***	0.131***
Place-Level Interactions										
Place Indicator (1 =Place)	--	--	--	--	--	--	--	--	4.149**	9.274***
x Percent Black	--	--	--	--	--	--	--	--	-0.009**	-0.002
x Percent Female-Headed	--	--	--	--	--	--	--	--	0.051*	0.030*
x Per Capita Income	--	--	--	--	--	--	--	--	-0.473***	-0.917***
x Percent College Degree	--	--	--	--	--	--	--	--	-0.108***	-0.205***
x Percent Unemployed	--	--	--	--	--	--	--	--	-0.111***	-0.092***
Constant	7.897***	14.002***	4.986***	5.804	4.712***	6.930***	8.345***	11.568***	3.348*	3.420*
R-Square	0.004	0.038	0.123	0.073	0.189	0.102	0.234	0.165	0.245	0.186

*** P-value < .001; ** P-value < .01; * P-value < .05

^ RA1 - Suitable Target, RA2 - Motivated Offender, RA3 - Lack of Capable Gaurdian

Table A.8. OLS Regression Results of Logged Total Crime Rates on an Integrated Ecological Theoretical Framework

	Model		Interactions	
	Model FI1		Model FI2	
	1990	2000	1990	2000
Independent Variables				
Popualtion Size	-0.122***	-0.299***	-0.186***	-0.232***
Popualtion Density	0.170	0.165***	0.247***	0.196***
Percent Black	0.000	0.008***	0.007**	0.005*
Resedential Segregation	0.326***	0.307***	0.313***	0.151*
Income per Capita	-0.243**	-0.191*	0.262	0.672***
Percent College Degree	0.021	0.011	0.001	0.027
Percent Unemployed	0.041***	0.017	0.109***	0.082***
Percent Female-Head HH	0.001	-0.013*	-0.038***	-0.022*
Percent Divorced	0.036***	0.297***	0.039***	0.234***
Percent Housing Own-Occ	-0.010***	-0.014***	-0.009***	-0.017***
Percent Housing pre-1940	-0.007***	-0.010***	-0.008***	-0.007***
Percent Below Poverty	0.001	-0.001	0.006*	0.004
Percent Under 18	0.008*	-0.010*	0.010**	0.013***
Percent b/w 18-24	0.002	0.007*	0.003	0.006*
Officers per 1k Pop	0.399***	0.088***	0.338***	-0.001
Northeast	0.049	-0.309***	0.057	-0.129*
Midwest	0.222***	-0.002	0.235***	0.152***
West	0.276***	0.206***	0.314***	0.259***
Adajcent Non-Metro	-0.325***	-0.369***	-0.330***	-0.272***
Non-Adajcent Non-Metro	-0.396***	-0.489***	-0.392***	-0.395***
Place-Level Interactions				
Place Indicator (1 =Place)	--	--	3.794**	7.589***
x Percent Black	--	--	-0.008**	-0.001
x Percent Female-Headed	--	--	0.045***	0.015
x Per Capita Income	--	--	-0.498***	-0.802***
x Percent College Degree	--	--	0.032	0.018*
x Percent Unemployed	--	--	-0.085**	-0.060
Constant	9.967***	11.577***	5.816***	2.465
R-Square	0.272	0.259	0.281	0.242

*** P-value < .001; ** P-value < .01; * P-value < .05

Table A.9. OLS Regression Results of Logged Property Crime Rates on an Integrated Ecological Theoretical Framework

	Model		Interactions	
	Model FI1		Model FI2	
	1990	2000	1990	2000
Independent Variables				
Popualtion Size	-0.122***	-0.130***	-0.184***	-0.170***
Popualtion Density	0.170***	0.184***	0.247***	0.200***
Percent Black	-0.001	0.008***	0.006*	0.010***
Resedential Segregation	0.323***	0.018	0.313***	0.049
Income per Capita	-0.224**	-0.231**	0.180	0.631***
Percent College Degree	0.031*	-0.017	0.023	0.045
Percent Unemployed	0.029*	0.060***	0.088***	0.160***
Percent Female-Head HH	0.001	-0.005	-0.034***	-0.021*
Percent Divorced	0.031***	0.362***	0.034***	0.330***
Percent Housing Own-Occ	-0.011***	-0.015***	-0.010***	-0.015***
Percent Housing pre-1940	-0.007***	-0.005***	-0.008***	-0.005***
Percent Below Poverty	0.001	0.003	0.005*	0.007*
Percent Under 18	0.007*	0.011*	0.008*	0.010*
Percent b/w 18-24	0.002	-0.003	0.004	-0.002
Officers per 1k Pop	0.397***	0.028*	0.389***	0.021
Northeast	-0.001	-0.089	0.005	-0.107
Midwest	0.213***	0.205***	0.223***	0.193***
West	0.238***	0.434***	0.272***	0.424***
Adajcent Non-Metro	-0.330***	-0.253***	-0.333***	-0.251***
Non-Adajcent Non-Metro	-0.402***	-0.340***	-0.399***	-0.336***
Place-Level Interactions				
Place Indicator (1 =Place)	--	--	2.828*	9.893***
x Percent Black	--	--	-0.008**	-0.001
x Percent Female-Headed	--	--	0.041***	0.019
x Per Capita Income	--	--	-0.386**	-0.993***
x Percent College Degree	--	--	0.015	-0.061
x Percent Unemployed	--	--	-0.073**	-0.126***
Constant	9.672***	8.226***	6.372***	-0.098
R-Square	0.272	0.225	0.282	0.236

*** P-value < .001; ** P-value < .01; * P-value < .05

Table A.10. OLS Regression Results of Logged Violent Crime Rates on an Integrated Ecological Theoretical Framework

	Model		Interactions	
	Model FI1		Model FI2	
	1990	2000	1990	2000
Independent Variables				
Popualtion Size	-0.056***	-0.130***	-0.127***	-0.170***
Popualtion Density	0.179***	0.184***	0.256***	0.200***
Percent Black	0.005***	0.008***	0.012***	0.010***
Resedential Segregation	0.264***	0.018	0.261***	0.049
Income per Capita	-0.420***	-0.231**	0.297	0.631***
Percent College Degree	-0.010	-0.017	0.029	0.045
Percent Unemployed	0.080***	0.060***	0.167***	0.160***
Percent Female-Head HH	0.002	-0.005	-0.033***	-0.021*
Percent Divorced	0.057***	0.362***	0.058***	0.330***
Percent Housing Own-Occ	-0.010***	-0.015***	-0.010***	-0.015***
Percent Housing pre-1940	-0.004***	-0.005***	-0.005***	-0.005***
Percent Below Poverty	0.001	0.003	0.007*	0.007*
Percent Under 18	0.013***	0.011*	0.014***	0.010*
Percent b/w 18-24	-0.004	-0.003	-0.002	-0.002
Officers per 1k Pop	0.445***	0.028*	0.413***	0.021
Northeast	0.065	-0.089	0.049	-0.107
Midwest	0.231***	0.205***	0.233***	0.193***
West	0.047***	0.434***	0.421***	0.424***
Adajcent Non-Metro	-0.306***	-0.253***	-.301***	-0.251***
Non-Adajcent Non-Metro	-0.324***	-0.340***	-0.318***	-0.336***
Place-Level Interactions				
Place Indicator (1 =Place)	--	--	6.005***	9.893***
x Percent Black	--	--	-0.007*	-0.001
x Percent Female-Headed	--	--	0.039***	0.019
x Per Capita Income	--	--	-0.687***	-0.993***
x Percent College Degree	--	--	-0.045	-0.061
x Percent Unemployed	--	--	-0.108***	-0.126***
Constant	8.908***	8.226***	2.526	-0.098
R-Square	0.263	0.225	0.274	0.236

*** P-value < .001; ** P-value < .01; * P-value < .05

Table A.11. List of Counties with Identified Place to Non-Place Contagious Diffusion by State, Type-Specific Crime and Crime Trend, 1990 – 2000

State	County Name	Diffusion Process by Crime Type					
		Total Crime		Property Crime		Violent Crime	
		High	Low	High	Low	High	Low
AL	Blount	--	--	--	X	--	--
	Calhoun	X	--	--	--	--	--
	Clay	--	X	--	--	--	--
	Cullman	--	--	--	X	--	--
	Lawrence	--	--	--	--	--	X
	Macon	X	--	--	--	--	--
	Russell	--	X	--	X	--	--
	Tuscaloosa	--	--	X	--	--	--
AZ	Maricopa	X	--	--	X	X	--
	Pima	X	--	X	--	X	--
	Pinal	X	--	X	--	X	--
AR	Carroll	--	X	--	X	--	X
	Clay	X	--	--	X	X	--
	Crittenden	X	--	X	--	--	--
	Franklin	--	--	--	--	--	X
	Johnson	--	--	--	--	--	X
	Lonoke	X	--	X	--	--	--
	Pulaski	X	--	X	--	--	--
	Saline	--	--	--	X	--	--
	Sebastian	X	--	--	--	--	--
	White	--	--	--	--	X	--
CA	Butte	--	--	X	--	--	--
	Fresno	--	X	--	X	X	--
	Kern	--	X	--	X	X	--
	Lake	--	--	--	--	--	X
	Madera	--	X	--	X	--	X
	Mendocino	--	--	--	--	--	X
	Merced	--	--	--	--	X	--
	Monterey	--	--	--	--	X	--
	Riverside	X	--	X	--	X	--
	San Bernardino	--	--	--	--	X	--
	San Diego	X	--	X	--	--	--
	San Joaquin	--	X	--	X	X	--
	Santa Cruz	X	--	X	--	--	--
	Shasta	--	--	--	--	--	X
	Stanislaus	--	--	--	--	X	--
	Tehama	--	--	--	--	X	--
	Tulare	--	X	--	X	--	X

Table A.11. Continued

State	County Name	Diffusion Process by Crime Type (Table A.11 Cont.)					
		Total Crime		Property Crime		Violent Crime	
		High	Low	High	Low	High	Low
CO	Adams	--	x	--	x	--	x
	Eagle	--	x	--	--	--	--
	El Paso	--	--	--	x	--	--
	Pueblo	x	--	--	--	--	--
	Yuma	x	--	x	--	--	--
CT	New Haven	x	--	--	--	--	--
DE	Kent	--	--	--	--	x	--
	New Castle	--	--	--	--	x	--
	Sussex	--	--	--	--	x	--
FL	Brevard	x	--	--	x	x	--
	Broward	x	--	--	x	x	--
	DeSoto	--	--	x	--	x	--
	Hardee	--	--	--	--	x	--
	Hernando	x	--	x	--	x	--
	Highlands	x	--	x	--	--	x
	Hillsborough	x	--	--	x	x	--
	Jefferson	x	--	x	--	x	--
	Lake	--	--	--	--	x	--
	Levy	--	--	--	--	--	x
	Madison	--	x	--	x	--	x
	Manatee	x	--	x	--	x	--
	Osceola	x	--	--	x	x	--
	Pasco	x	--	x	--	x	--
	St. Johns	x	--	x	--	x	--
	St. Lucie	x	--	--	x	x	--
	Santa Rosa	x	--	x	--	x	--
	Sumter	--	--	--	x	--	--
	Taylor	--	--	--	--	x	--
	Volusia	x	--	x	--	--	--
GA	Berrien	--	x	x	--	x	--
	Brantley	--	x	--	x	--	x
	Burke	--	--	--	x	--	--
	Calhoun	--	x	--	x	--	--
	Candler	--	x	--	x	--	--
	Catoosa	--	--	--	x	--	--
	Chatham	x	--	x	--	--	--
	Chattahoochee	--	--	--	--	--	x
	Clay	x	--	x	--	x	--
	Clayton	x	--	x	--	--	--
	Cobb	x	--	x	--	--	--

Table A.11. Continued

State	County Name	Diffusion Process by Crime Type (Table A.11 Cont.)					
		Total Crime		Property Crime		Violent Crime	
		High	Low	High	Low	High	Low
	Fulton	X	--	X	--	X	--
	Gilmer	--	--	--	--	X	--
	Habersham	X	--	X	--	--	--
	Jasper	--	X	--	X	--	X
	Jenkins	--	X	--	X	--	--
	Madison	--	X	--	X	X	--
	Marion	--	X	--	X	X	--
	Miller	--	X	--	X	--	X
	Montgomery	X	--	--	--	X	--
	Murray	--	--	X	--	--	--
	Pickens	--	X	--	X	--	--
	Pierce	--	--	--	--	--	X
	Rabun	--	X	--	X	--	X
	Randolph	--	X	--	X	--	--
	Schley	--	X	--	X	--	--
	Stewart	X	--	X	--	--	X
	Talbot	--	X	--	X	X	--
	Taylor	--	X	--	X	--	X
	Treutlen	--	--	--	--	X	--
	Troup	X	--	X	--	--	--
	Washington	--	X	--	X	--	--
	Wheeler	X	--	--	--	--	X
	White	--	--	--	--	--	X
	Wilkinson	--	--	--	X	--	--
	Worth	--	X	--	X	X	--
ID	Fremont	--	--	--	--	X	--
IN	Howard	X	--	X	--	X	--
	Martin	--	X	--	--	--	--
IA	Hancock	--	--	--	--	X	--
	Lyon	--	--	--	--	X	--
	Scott	X	--	--	--	X	--
KS	Atchison	X	--	X	--	X	--
	Barber	--	--	--	X	--	--
	Chautauqua	--	X	--	--	--	--
	Decatur	--	X	--	--	--	X
	Ellsworth	X	--	X	--	--	--
	Geary	--	--	--	--	X	--
	Linn	--	X	--	X	--	--
	McPherson	--	X	--	--	X	--
	Republic	--	X	--	X	--	--

Table A.11. Continued

State	County Name	Diffusion Process by Crime Type (Table A.11 Cont.)					
		Total Crime		Property Crime		Violent Crime	
		High	Low	High	Low	High	Low
	Rooks	--	x	x	--	--	--
	Scott	--	--	x	--	x	--
	Sheridan	--	x	--	x	--	--
	Stafford	x	--	--	--	--	--
LA	Tangipahoa	--	--	x	--	--	--
	Winn	--	--	--	x	--	--
MD	Anne Arundel	x	--	x	--	x	--
	Cecil	--	--	--	--	x	--
	Dorchester	--	--	--	--	x	--
	Somerset	--	--	--	--	--	x
	Talbot	--	--	--	--	--	x
	Wicomico	--	--	--	--	x	--
MI	Berrien	--	--	--	--	x	--
	Calhoun	--	--	--	--	--	x
	Cass	--	--	--	--	x	--
	Chippewa	--	--	--	--	x	--
	Crawford	--	--	--	--	--	x
	Genesee	x	--	x	--	x	--
	Ionia	--	--	--	--	x	--
	Jackson	x	--	--	--	x	--
	Livingston	x	--	x	--	--	--
	Macomb	x	--	--	--	--	--
	Montcalm	--	--	--	--	--	x
	Muskegon	x	--	x	--	x	--
	Washtenaw	x	--	x	--	x	--
MN	Meeker	--	--	--	--	x	--
	Wabasha	--	--	--	--	--	x
	Washington	x	--	x	--	--	--
	Winona	--	--	--	--	x	--
MS	Adams	--	x	--	--	x	--
	Chickasaw	x	--	x	--	x	--
	Noxubee	x	--	--	x	--	--
	Warren	--	x	--	x	--	--
MO	Butler	--	--	--	--	x	--
	Dunklin	--	--	--	--	x	--
	Jefferson	x	--	x	--	--	--
	Warren	--	x	--	x	x	--
MT	Flathead	--	--	x	--	--	--
NE	Boone	x	--	x	--	--	--
	Dawes	--	--	--	--	x	--

Table A.11. Continued

State	County Name	Diffusion Process by Crime Type (Table A.11 Cont.)					
		Total Crime		Property Crime		Violent Crime	
		High	Low	High	Low	High	Low
	Holt	--	--	--	x	--	--
	Keith	--	--	--	--	x	--
	Nuckolls	--	x	--	x	--	x
NV	Washoe	--	--	--	--	x	--
NJ	Camden	--	--	--	--	x	--
	Salem	--	--	--	--	x	--
NM	Cibola	--	--	--	--	x	--
	Luna	--	--	--	--	x	--
	McKinley	x	--	x	--	x	--
	Mora	--	--	--	--	--	x
NY	Cayuga	--	x	--	--	--	--
	Franklin	--	--	--	--	x	--
	Jefferson	--	--	x	--	--	x
	Tompkins	--	--	--	--	--	x
	Warren	--	--	--	--	x	--
	Washington	--	--	--	--	--	x
NC	Avery	--	x	--	x	--	x
	Beaufort	--	--	--	--	x	--
	Bertie	--	--	x	--	--	--
	Cleveland	--	x	--	x	--	--
	Columbus	--	x	--	x	--	--
	Cumberland	x	--	--	x	x	--
	Dare	x	--	x	--	--	--
	Forsyth	x	--	x	--	x	--
	Guilford	--	x	--	x	--	--
	Lincoln	--	--	--	--	x	--
	Mecklenburg	--	x	--	x	x	--
	Mitchell	x	--	x	--	--	--
	Orange	--	--	--	x	--	--
	Pitt	--	x	--	--	--	--
	Richmond	--	--	x	--	--	--
	Robeson	x	--	x	--	--	--
	Rockingham	--	--	--	--	x	--
	Scotland	--	--	x	--	--	--
	Vance	x	--	x	--	x	--
	Wayne	x	--	x	--	x	--
OH	Butler	--	--	--	--	x	--
	Champaign	--	--	--	--	x	--
	Clark	--	--	--	--	x	--
	Morgan	--	x	--	x	--	x

Table A.11. Continued

State	County Name	Diffusion Process by Crime Type (Table A.11 Cont.)					
		Total Crime		Property Crime		Violent Crime	
		High	Low	High	Low	High	Low
OK	Haskell	--	--	--	X	--	--
	Kay	--	--	--	--	X	--
OR	Jefferson	--	--	--	--	X	--
	Lane	X	--	X	--	X	--
	Linn	X	--	X	--	X	--
	Morrow	--	--	--	X	--	--
	Wallowa	--	X	--	X	--	X
PA	Crawford	X	--	X	--	--	X
	Dauphin	--	--	--	--	X	--
	Jefferson	--	--	--	--	--	X
	Lebanon	--	--	--	--	--	X
RI	Newport	--	--	--	--	X	--
SC	Abbeville	--	--	X	--	--	--
	Anderson	--	X	--	--	X	--
	Barnwell	--	--	--	--	X	--
	Berkeley	X	--	X	--	X	--
	Charleston	--	--	--	--	--	X
	Chester	X	--	--	--	X	--
	Darlington	X	--	X	--	X	--
	Edgefield	--	--	--	--	X	--
	Fairfield	X	--	--	--	X	--
	Florence	--	X	--	X	--	X
	Greenwood	X	--	--	--	X	--
	Horry	X	--	X	--	X	--
	Lancaster	X	--	--	--	X	--
	Laurens	--	--	--	--	X	--
	Lexington	--	--	X	--	--	--
	Marion	--	--	--	--	X	--
	Newberry	--	--	--	X	--	--
	Oconee	--	--	--	--	X	--
	Pickens	--	--	--	--	X	--
	Richland	--	--	--	X	--	--
	Williamsburg	--	--	--	--	--	X
SD	Beadle	--	X	--	--	--	--
	Gregory	--	X	--	X	--	X
	Hutchinson	--	--	--	--	--	X
	McPherson	--	--	--	X	--	--
	Minnehaha	--	--	--	--	X	--
TN	Carroll	--	X	--	X	--	--
	Decatur	--	X	--	X	--	X

Table A.11. Continued

State	County Name	Total Crime High	Total Crime Low	Property Crime High	Property Crime Low	Violent Crime High	Violent Crime Low
	Franklin	--	X	--	X	--	X
	Giles	X	--	X	--	--	--
	Henderson	X	--	X	--	--	--
	Humphreys	--	--	--	--	X	--
	Lawrence	X	--	X	--	--	--
	Madison	--	--	--	--	X	--
	Polk	--	--	--	--	--	X
	Sumner	--	--	--	--	X	--
	Wayne	--	X	--	X	--	X
	Williamson	--	--	--	--	X	--
TX	Bell	--	X	--	X	--	--
	Castro	--	--	--	--	X	--
	Deaf Smith	--	--	--	--	X	--
	Fort Bend	--	--	--	--	X	--
	Galveston	--	--	--	--	X	--
	Gonzales	--	--	--	--	X	--
	Harrison	X	--	X	--	X	--
	Hidalgo	X	--	--	--	--	--
	Hunt	X	--	--	--	X	--
	Jones	X	--	X	--	X	--
	Kaufman	X	--	X	--	X	--
	Marion	--	--	--	--	X	--
	Matagorda	X	--	X	--	X	--
	Navarro	--	--	--	--	X	--
	Orange	--	--	--	--	X	--
	Sabine	--	X	--	X	--	--
	Tarrant	X	--	--	--	--	--
	Taylor	X	--	--	X	X	--
	Wharton	X	--	--	--	X	--
	Wheeler	--	--	X	--	--	--
	Wise	--	X	--	--	--	--
UT	Salt Lake	--	X	--	X	--	--
VA	Dickenson	--	X	--	X	--	--
	Fairfax	X	--	--	--	--	--
	Lee	X	--	X	--	--	--
	Lunenburg	--	X	--	X	--	--
	Orange	--	--	--	--	X	--
	Page	X	--	X	--	X	--
	Shenandoah	--	X	--	X	--	X
WA	Clark	--	X	--	--	X	--

Table A.11. Continued

State	County Name	Total Crime High	Total Crime Low	Property Crime High	Property Crime Low	Violent Crime High	Violent Crime Low
	Cowlitz	--	X	--	--	--	X
	Garfield	--	X	--	X	--	--
	Grant	X	--	X	--	X	--
	Jefferson	--	--	--	--	X	--
	Kitsap	X	--	X	--	X	--
	Kittitas	--	X	--	X	--	--
	Mason	X	--	--	--	X	--
	Pacific	--	--	--	--	X	--
	Pend Oreille	--	--	X	--	--	--
	Skagit	--	X	--	X	--	X
	Snohomish	--	--	--	--	X	--
	Walla Walla	X	--	--	--	X	--
	Whatcom	--	X	--	--	--	--
	Whitman	--	--	--	--	X	--
	Yakima	--	X	--	X	X	--
WV	Boone	--	X	--	X	--	--
	Braxton	--	X	--	X	--	--
	Calhoun	--	X	--	--	--	--
	Greenbrier	--	X	--	X	--	X
	Hardy	--	X	--	X	--	X
	Logan	--	X	--	X	--	--
	Mason	--	X	--	X	--	--
	Mingo	--	X	--	X	--	--
	Pleasants	--	X	X	--	--	--
	Randolph	--	X	--	X	--	--
	Ritchie	--	X	--	X	--	--
	Roane	--	X	--	--	--	--
	Tucker	--	X	--	X	--	--
WI	Dunn	--	--	--	--	--	X
	Iowa	--	--	--	--	X	--
	Iron	--	X	--	--	--	--
WY	Laramie	--	--	X	--	--	--
	Natrona	X	--	--	X	X	--

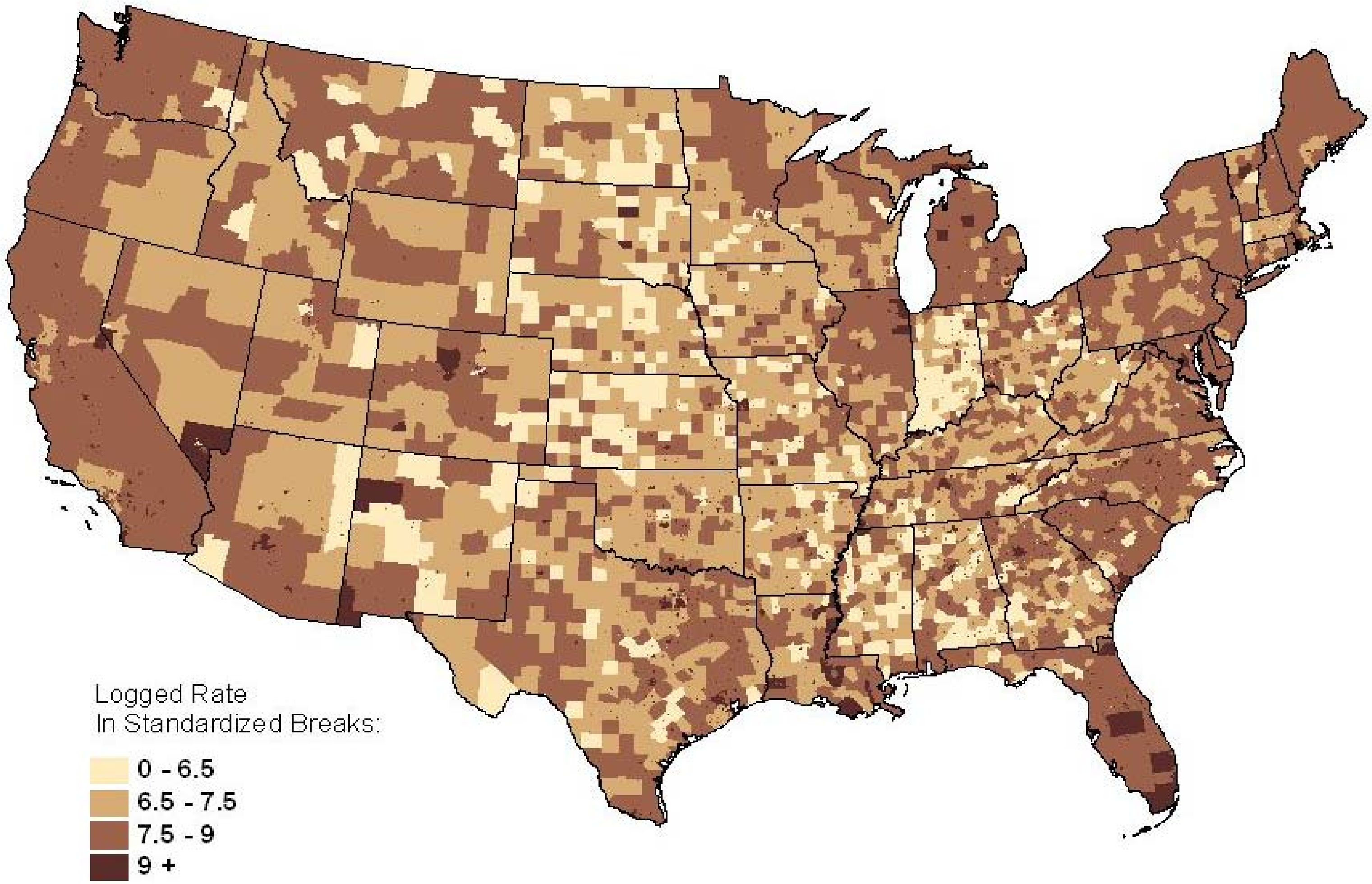


Figure A.1. Logged Total Crime Rate per 100,000 Population, 1990

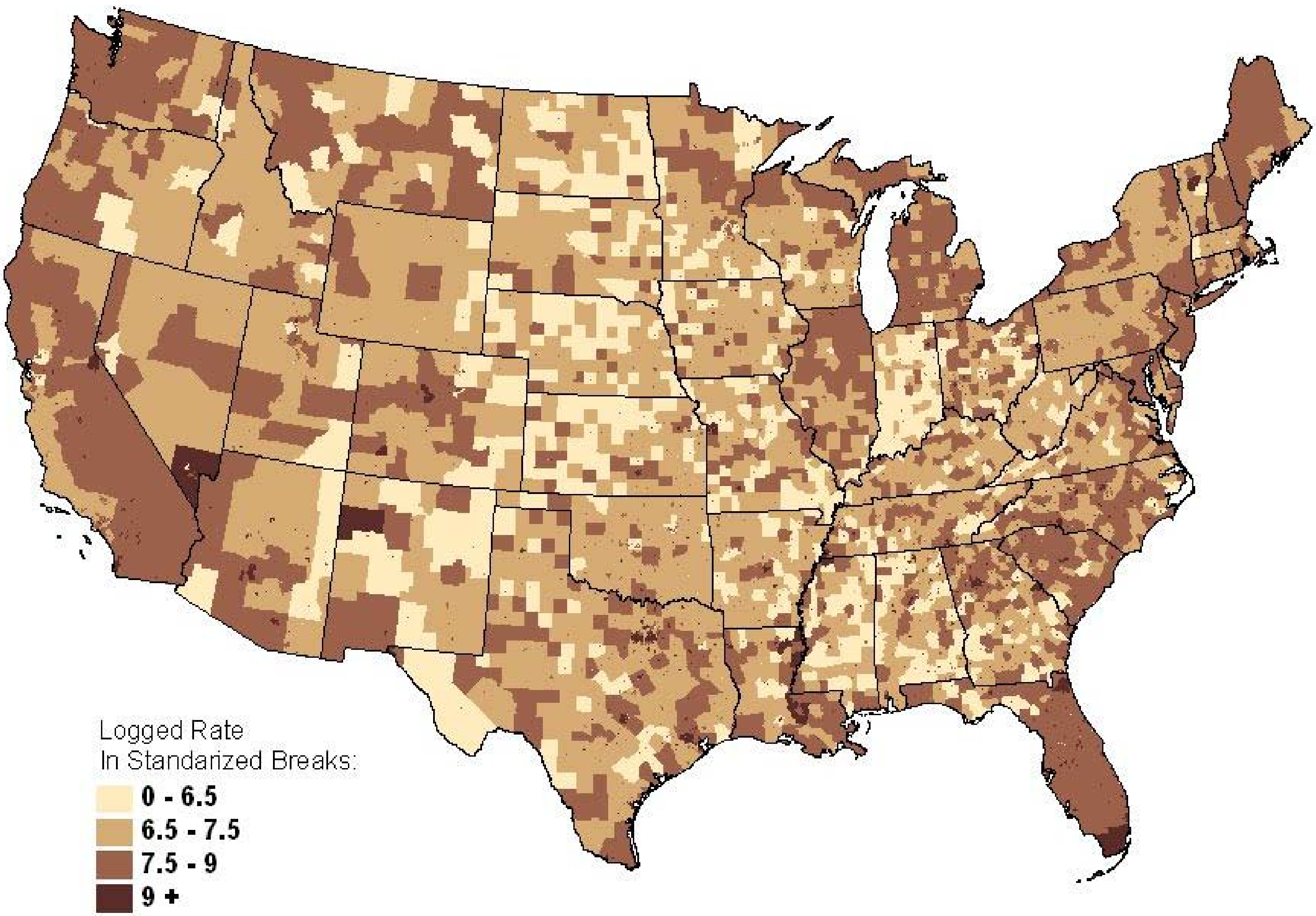


Figure A.2. Logged Property Crime Rate per 100,000 Population, 1990

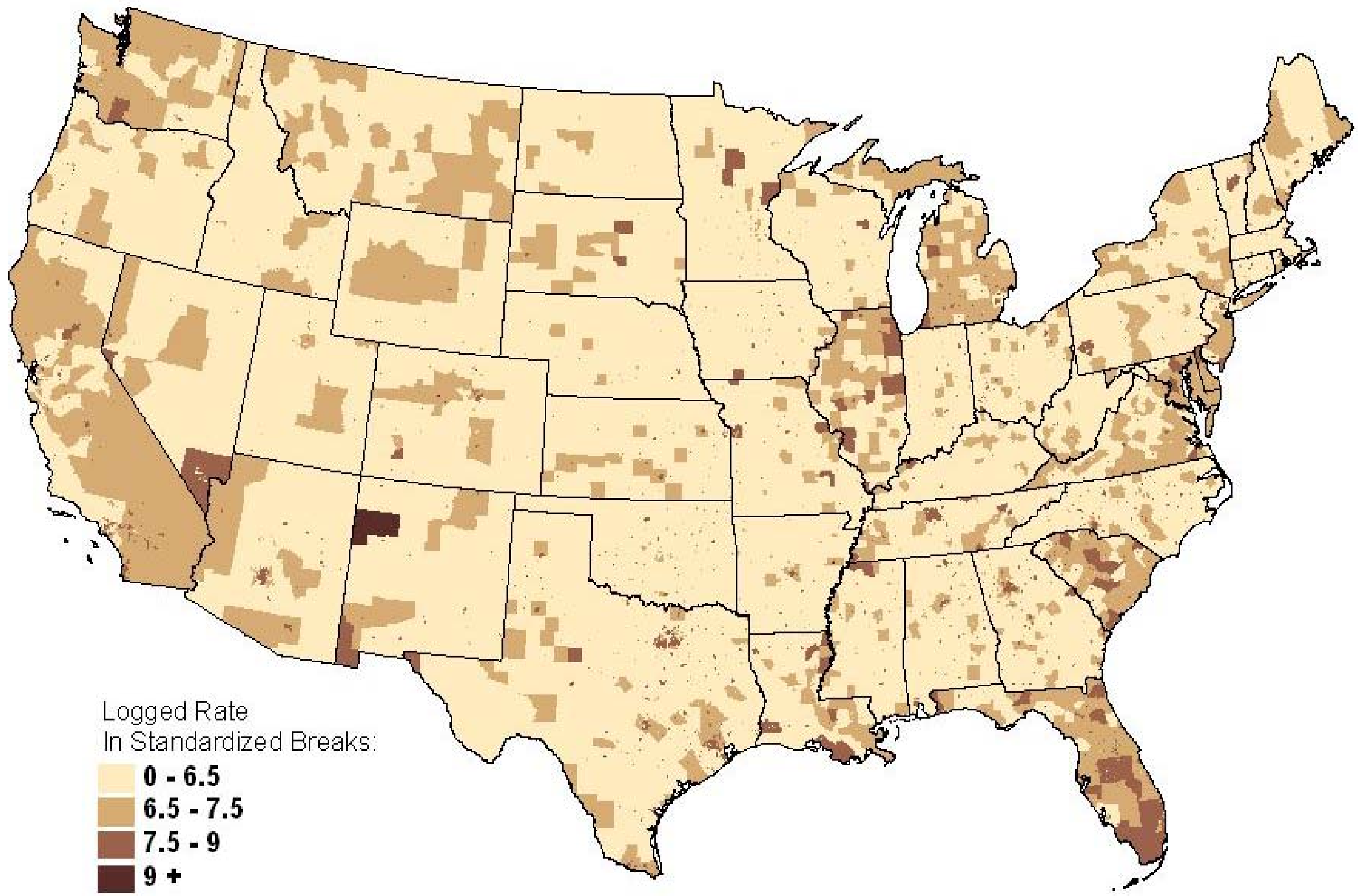


Figure A.3. Logged Violent Crime Rate per 100,000 Population, 1990

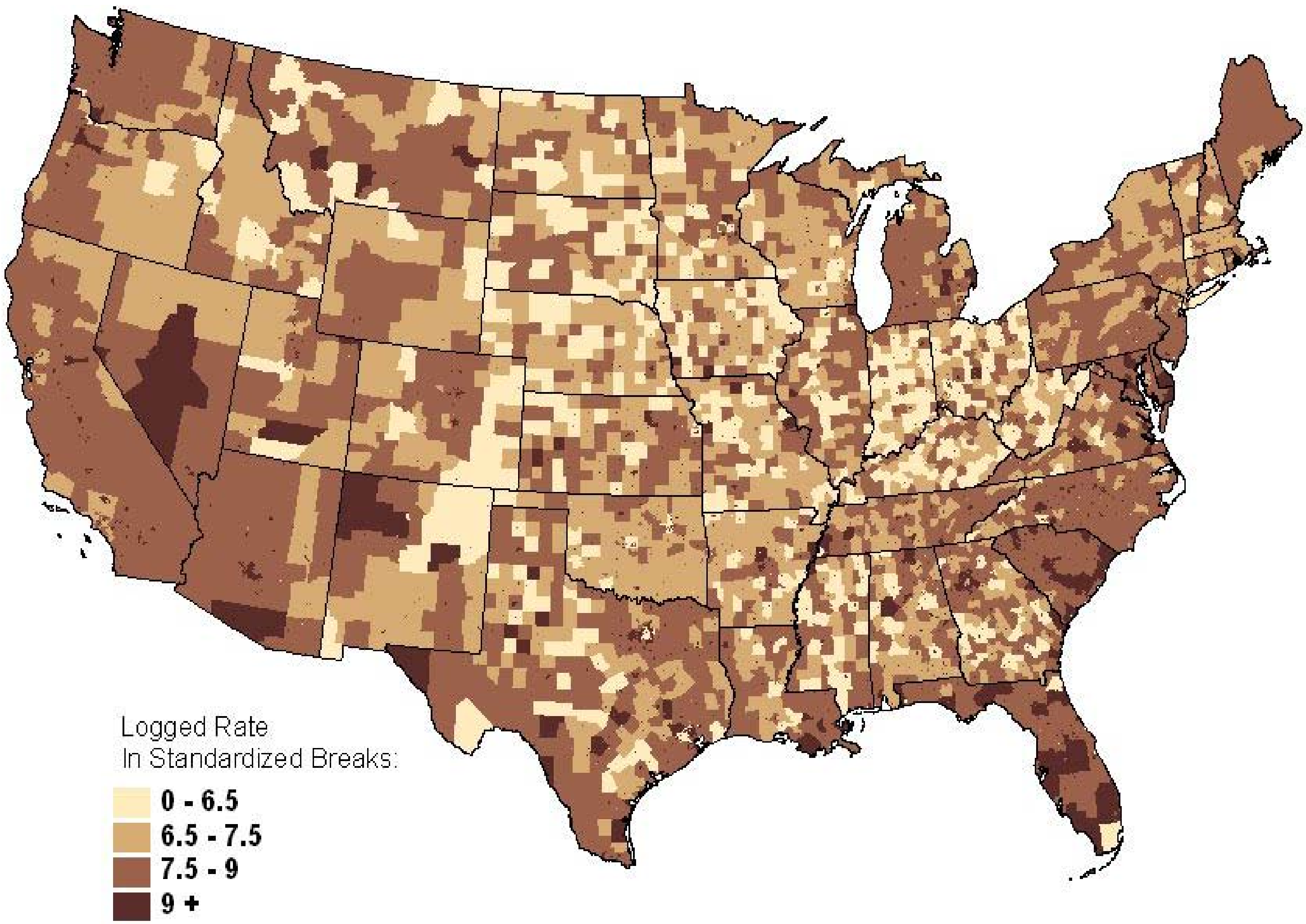


Figure A.4. Logged Total Crime Rate per 100,000 Population, 2000

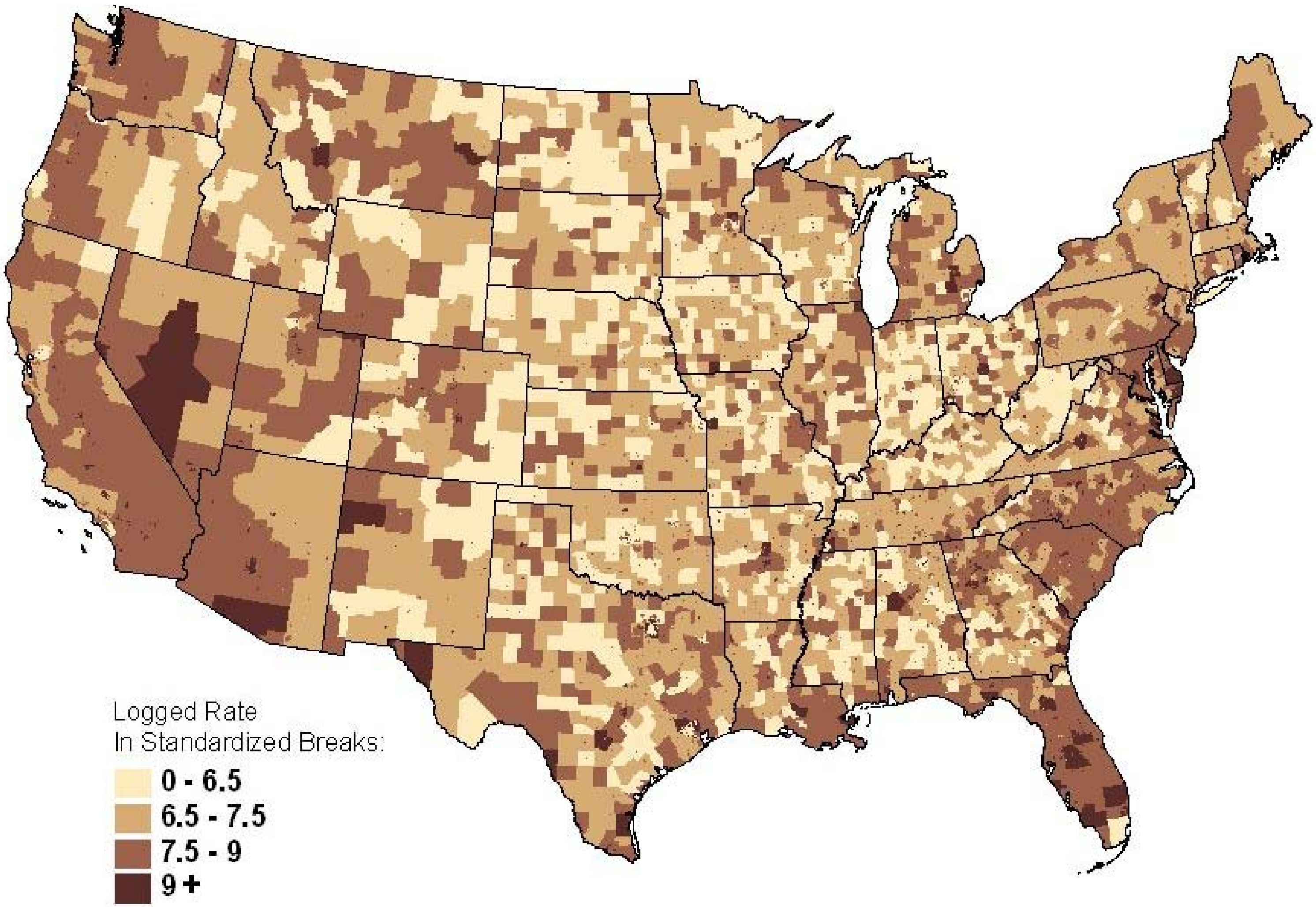


Figure A.5. Logged Property Crime Rate per 100,000 Population, 2000

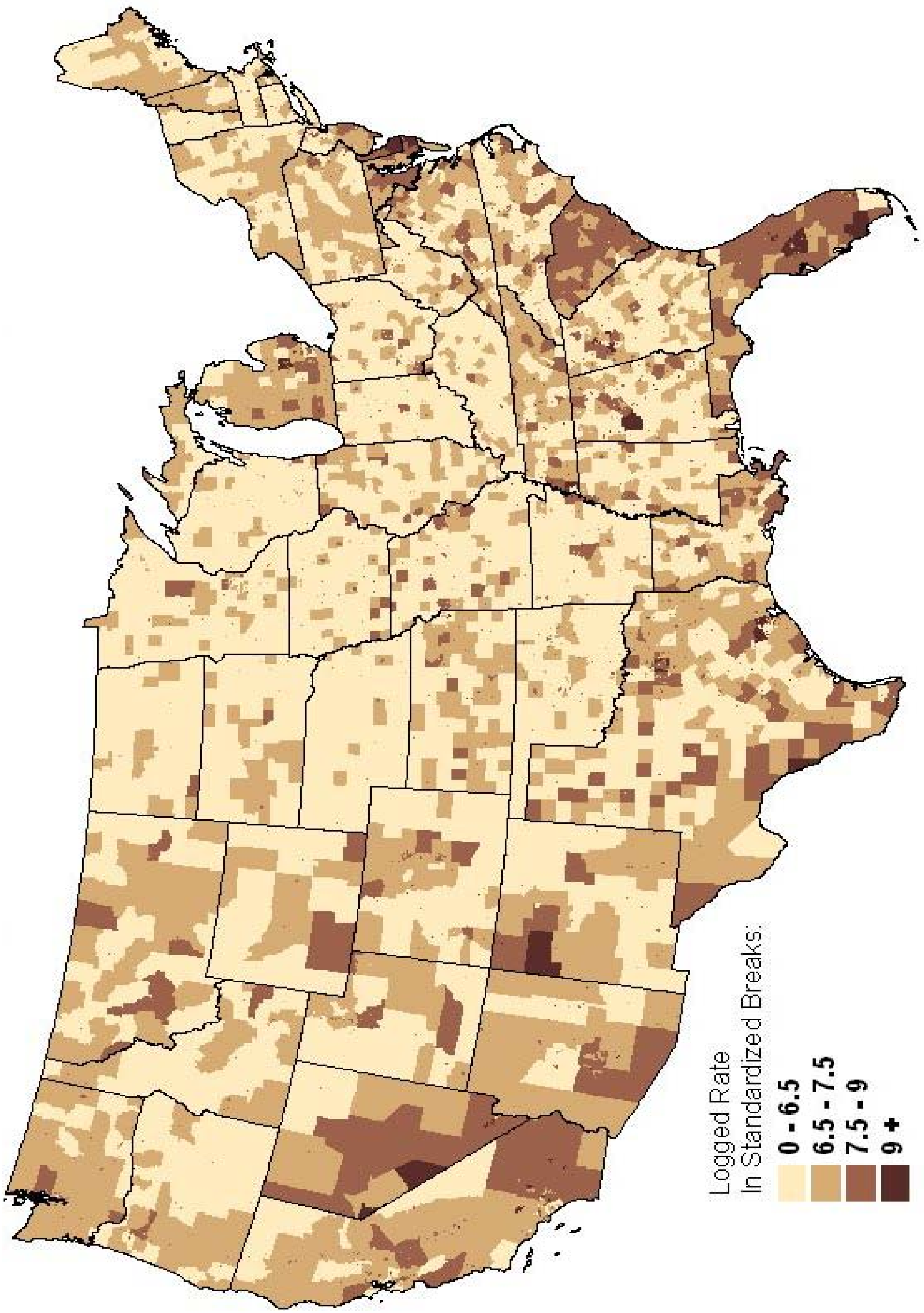


Figure A.6. Logged Violent Crime Rate per 100,000 Population, 2000

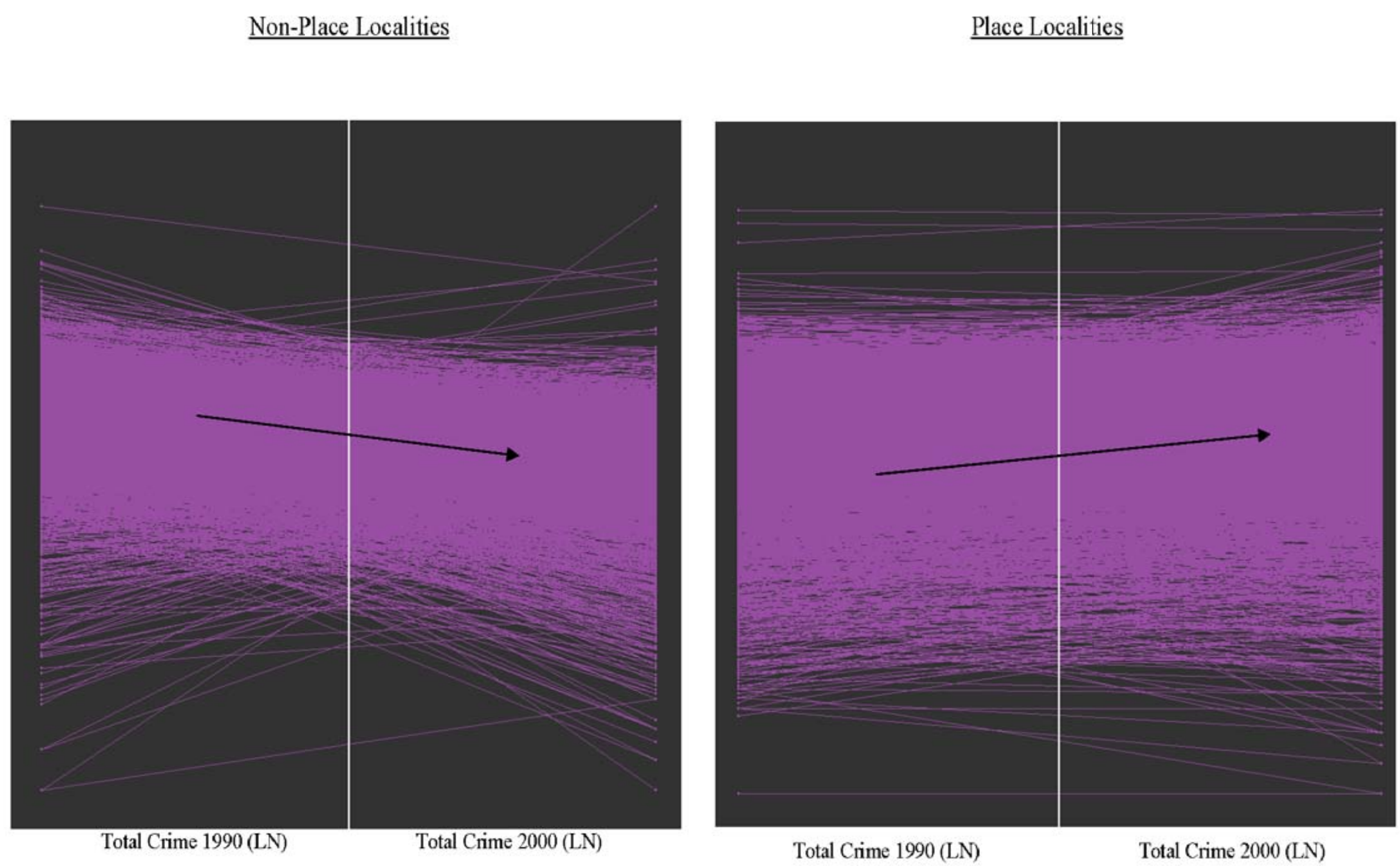


Figure A.7. Parallel Coordinate Plots Identifying General Temporal Trends in the Logged Total Crime Rate, 1990 – 2000

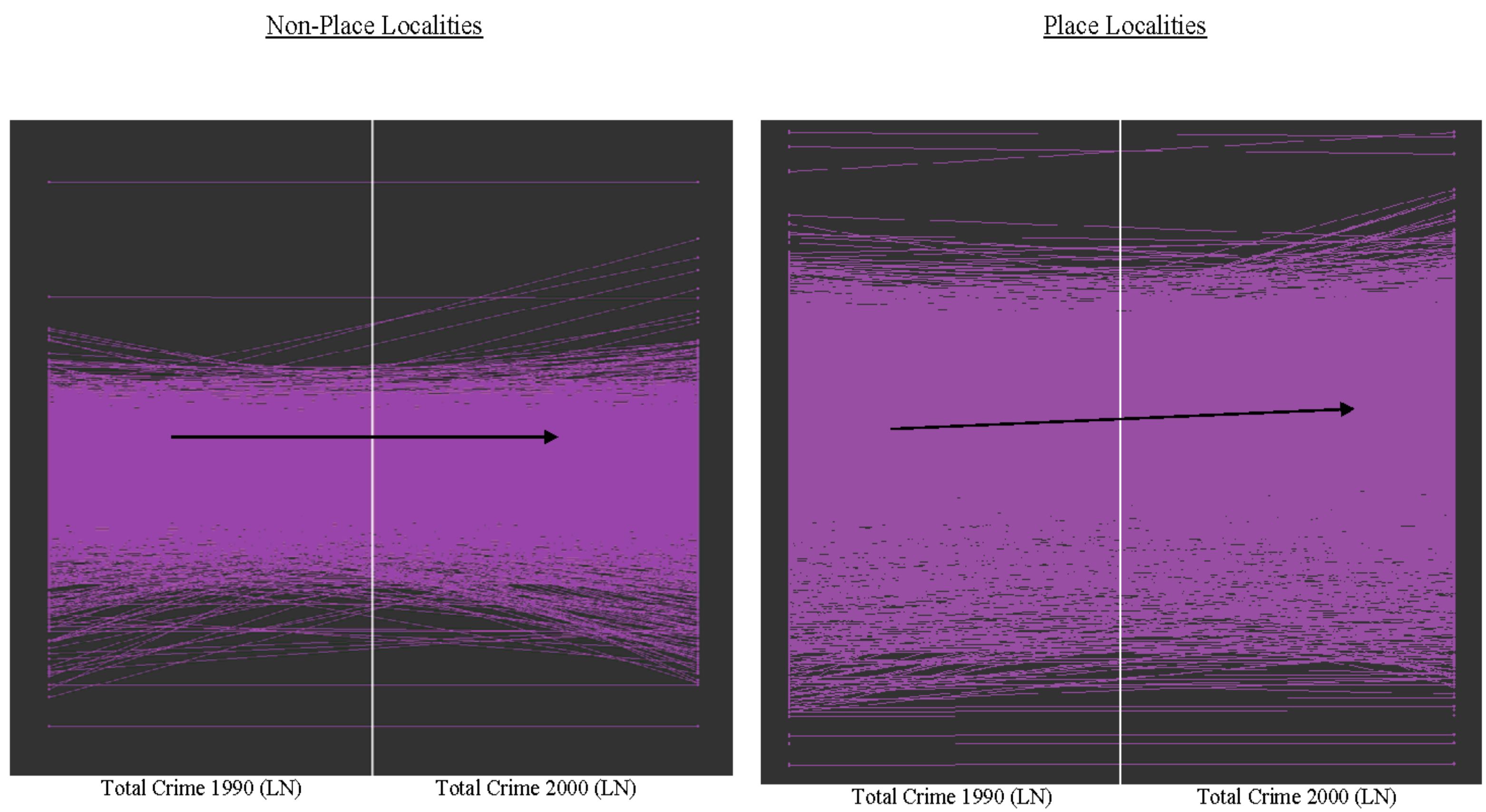


Figure A.8. Parallel Coordinate Plots Identifying General Temporal Trends in the Logged Property Crime Rate, 1990 – 2000

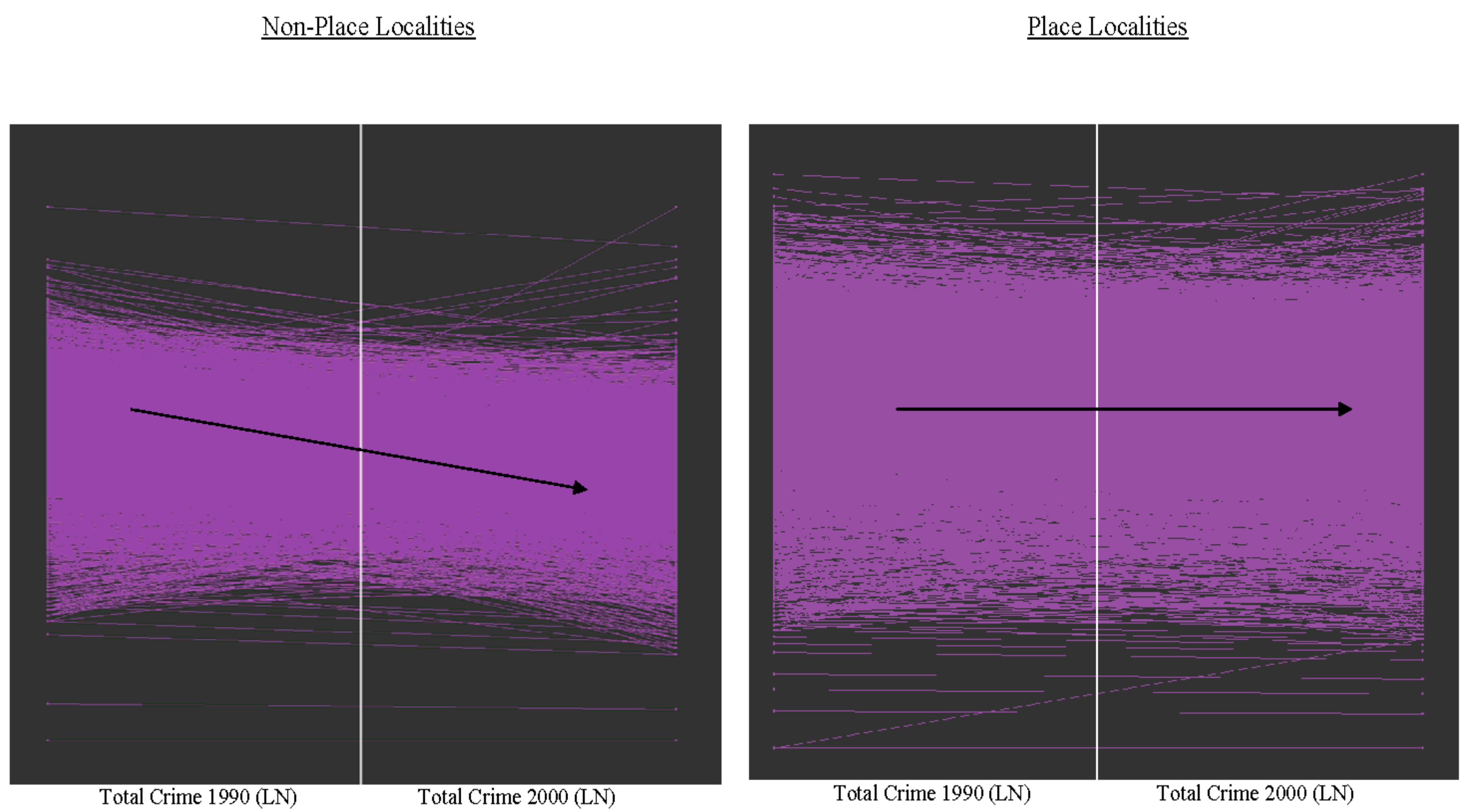
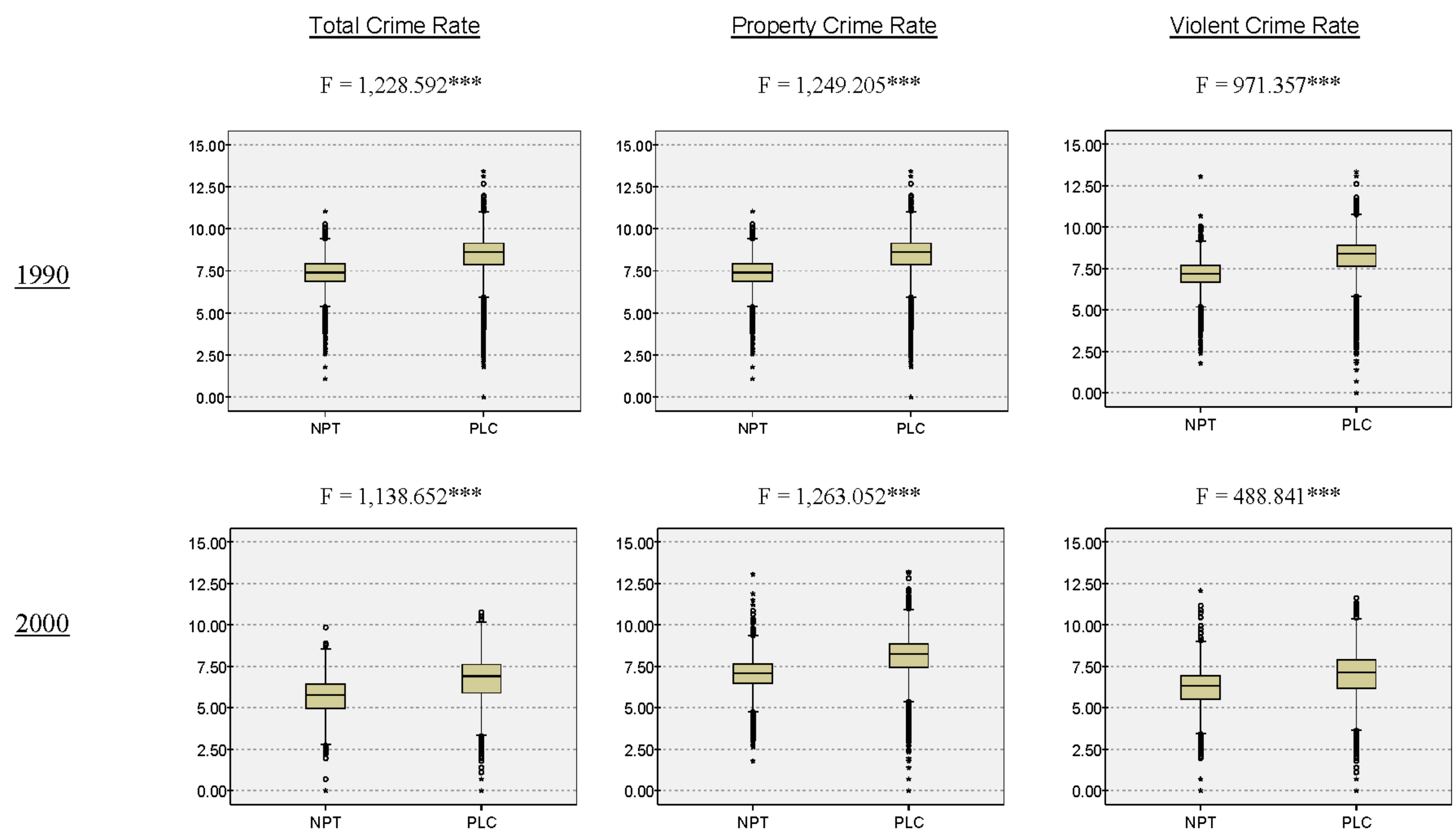
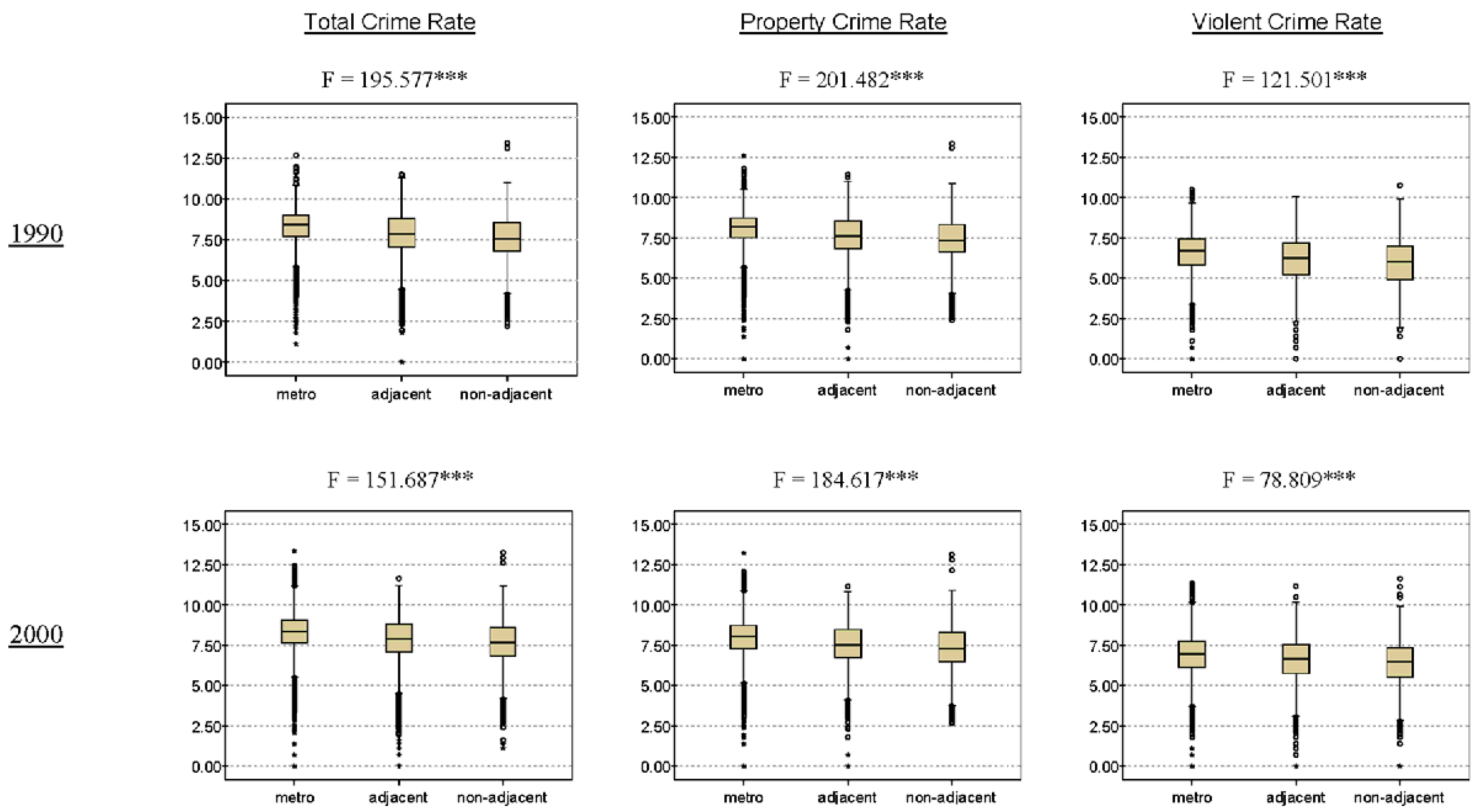


Figure A.9. Parallel Coordinate Plots Identifying General Temporal Trends in the Logged Violent Crime Rate, 1990 – 2000



*NPT = Non-Place Territory; PLC = Place

Figure A.10. Boxplots Examining Mean Differences in Type-Specific Logged Crime Rate by Place-Level Geography, 1990 & 2000



*Metro = Metropolitan; Adjacent = Adjacent Non-Metropolitan; Non-Adjacent = Non-Adjacent Non-Metropolitan

Figure A.11. Boxplots Examining Mean Differences in Type-Specific Logged Crime Rate by Metropolitan Status, 1990 & 2000

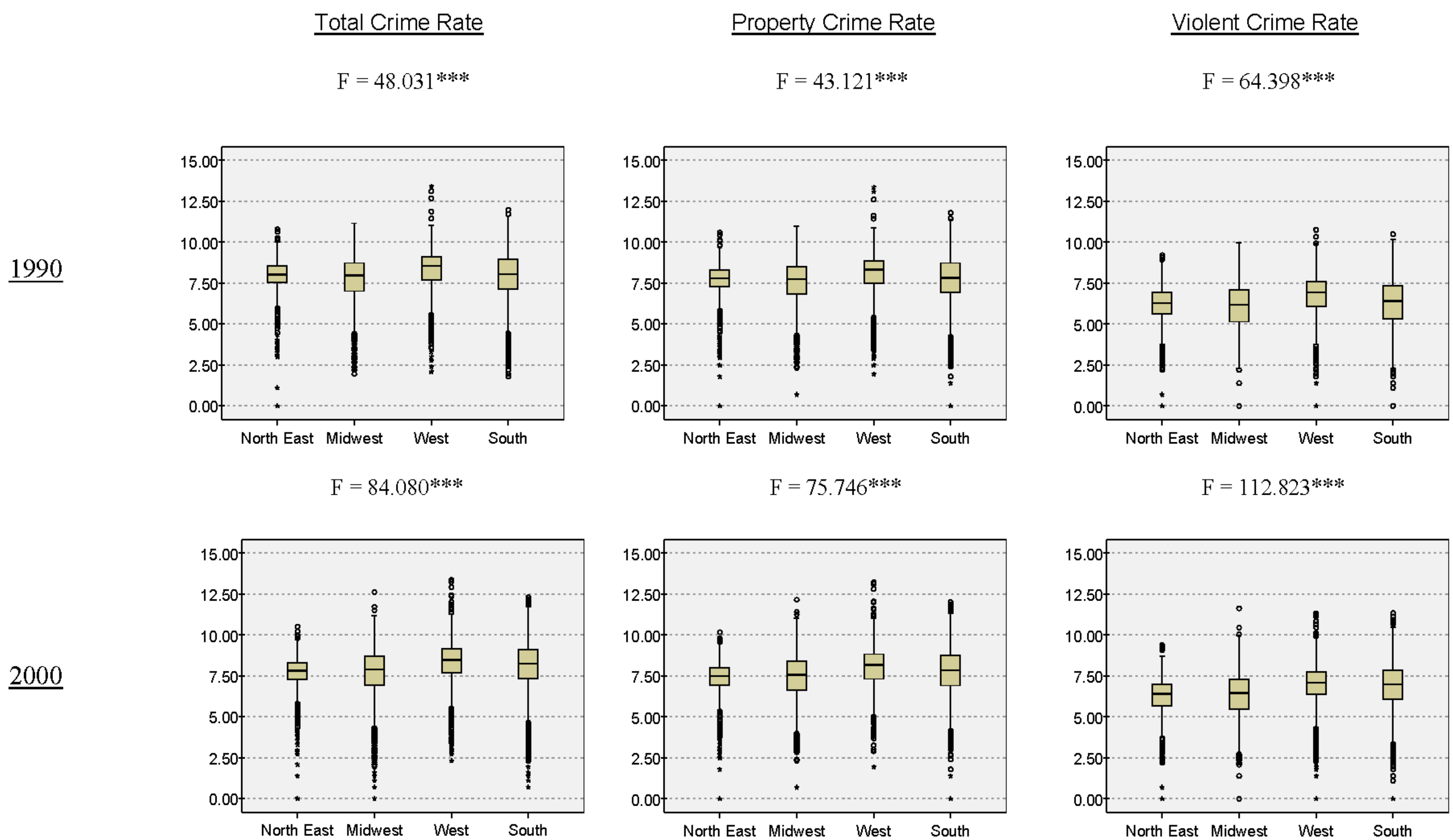


Figure A.12. Boxplots Examining Mean Differences in Type-Specific Logged Crime Rate by U.S. Census Region, 1990 & 2000

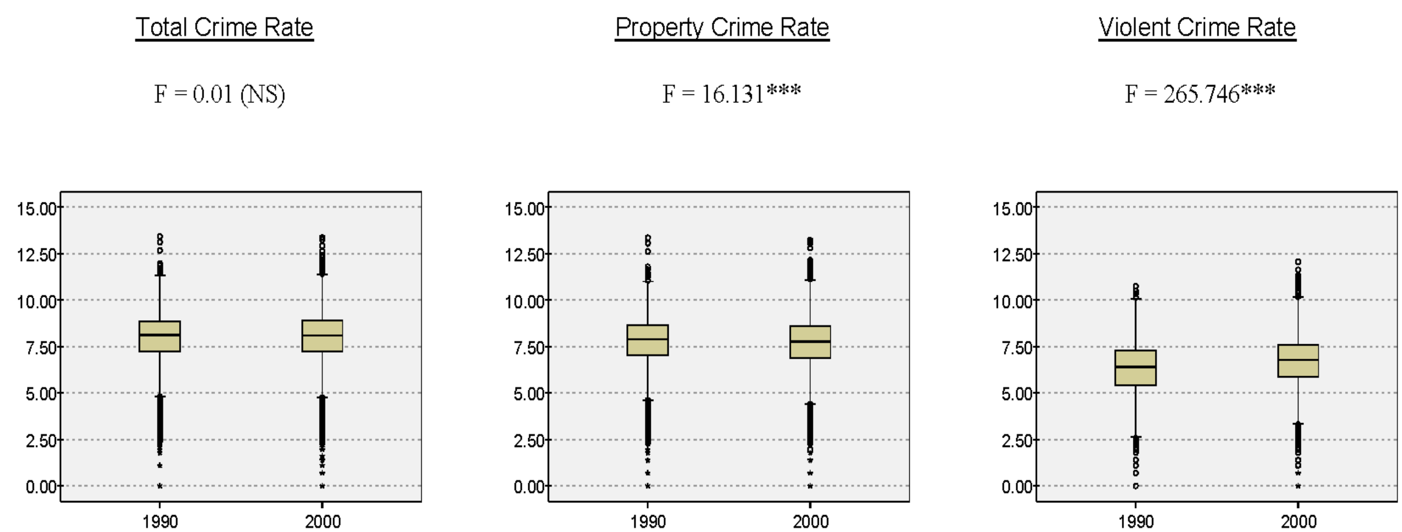
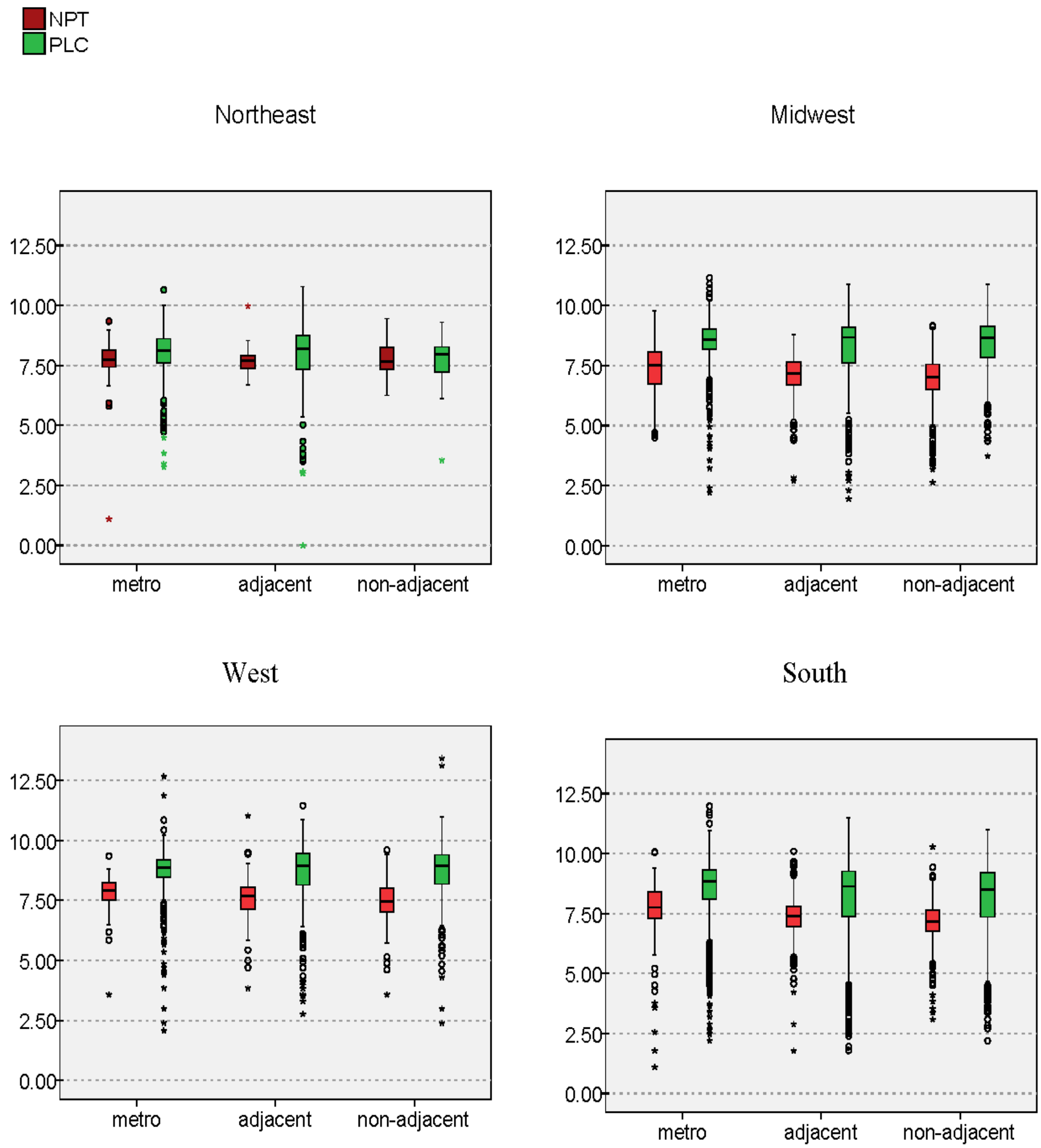
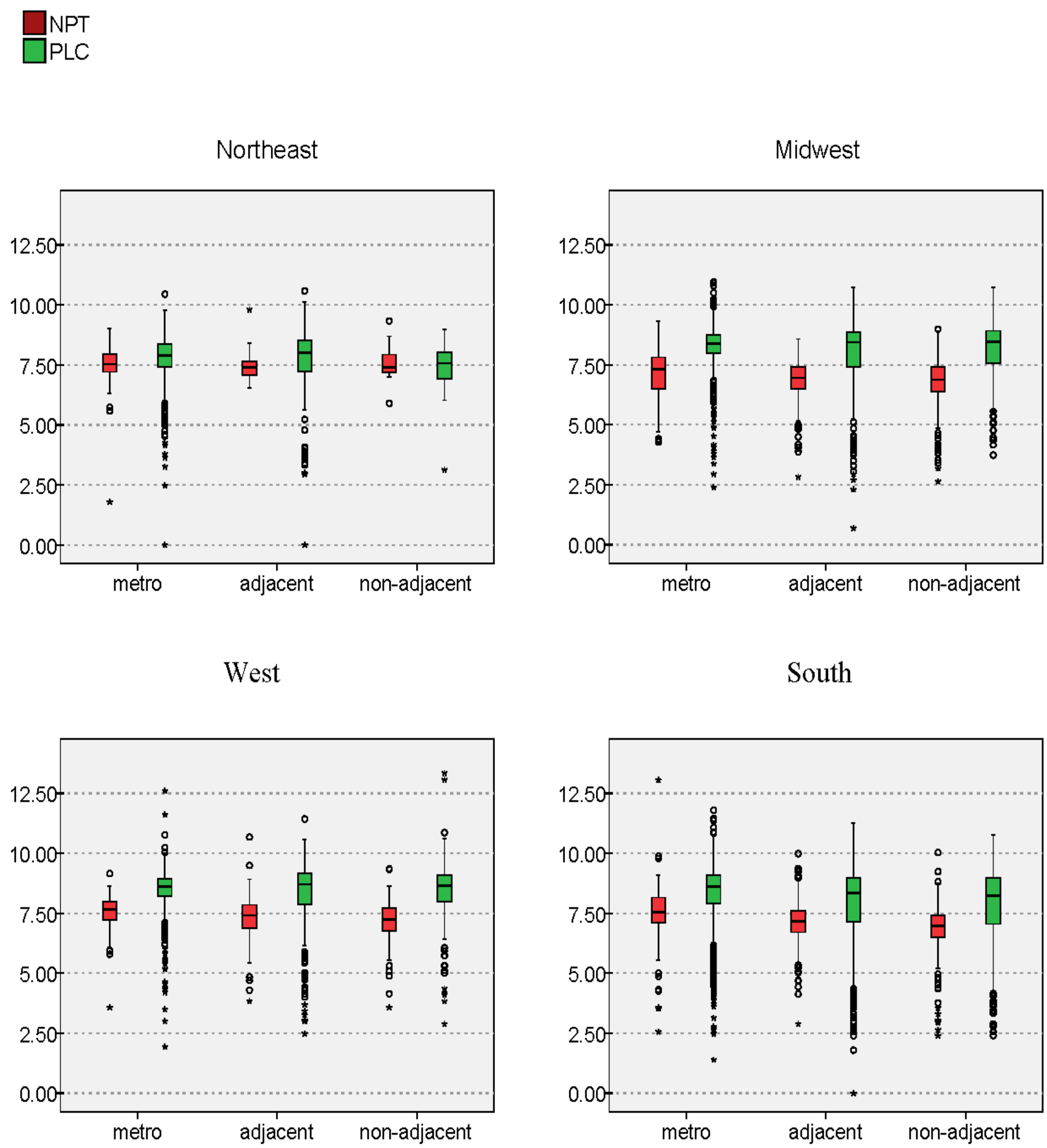


Figure A.13. Boxplots Examining Mean Differences in Type-Specific Logged Crime Rate by Temporal Period, 1990 & 2000



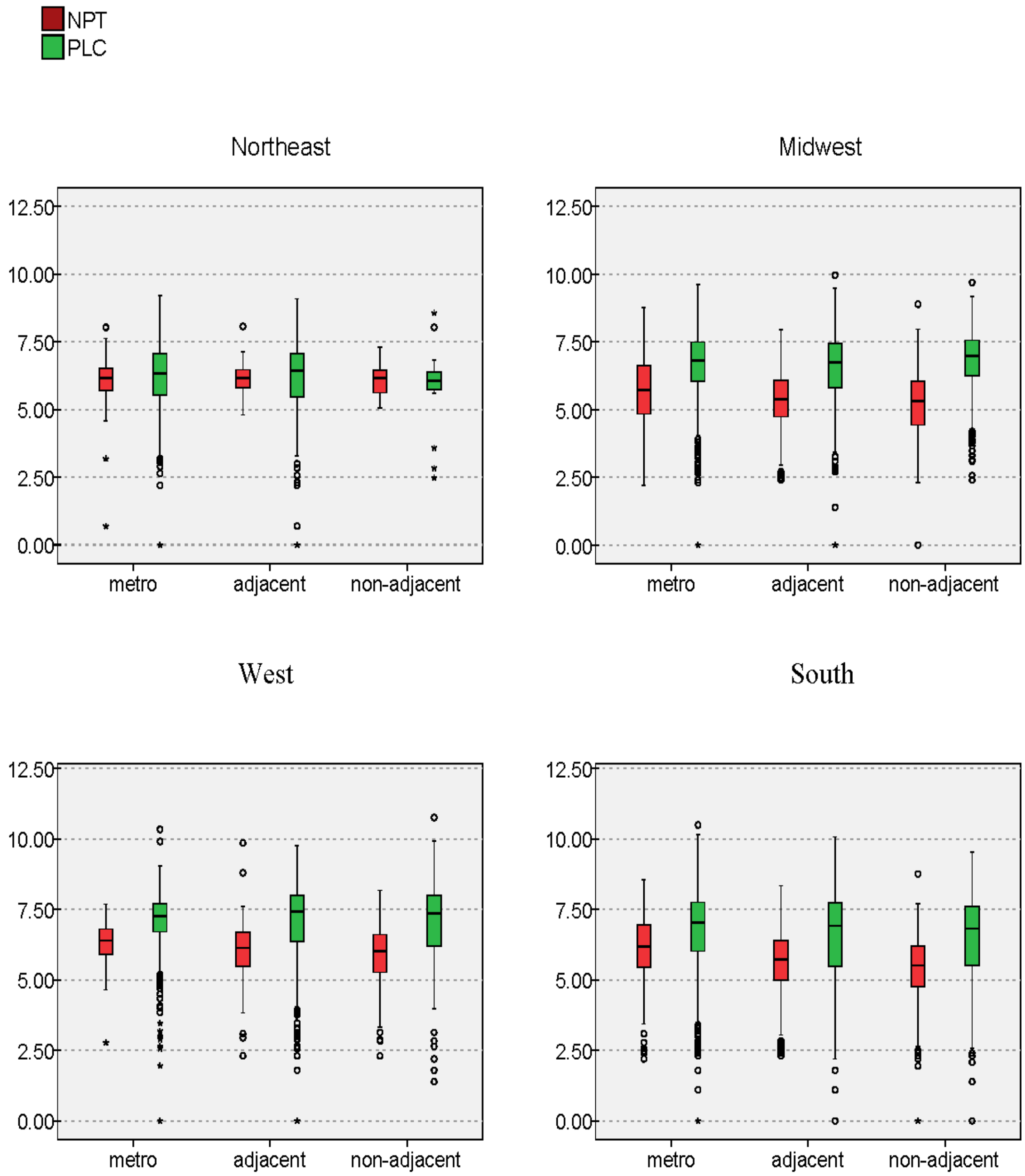
*Metro = Metropolitan; Adjacent = Adjacent Non-Metropolitan; Non-Adjacent = Non-Adjacent Non-Metropolitan

Figure A.14. Boxplots Examining Mean Differences in the Logged Total Crime Rate by U.S. Region and Metropolitan Status, 1990



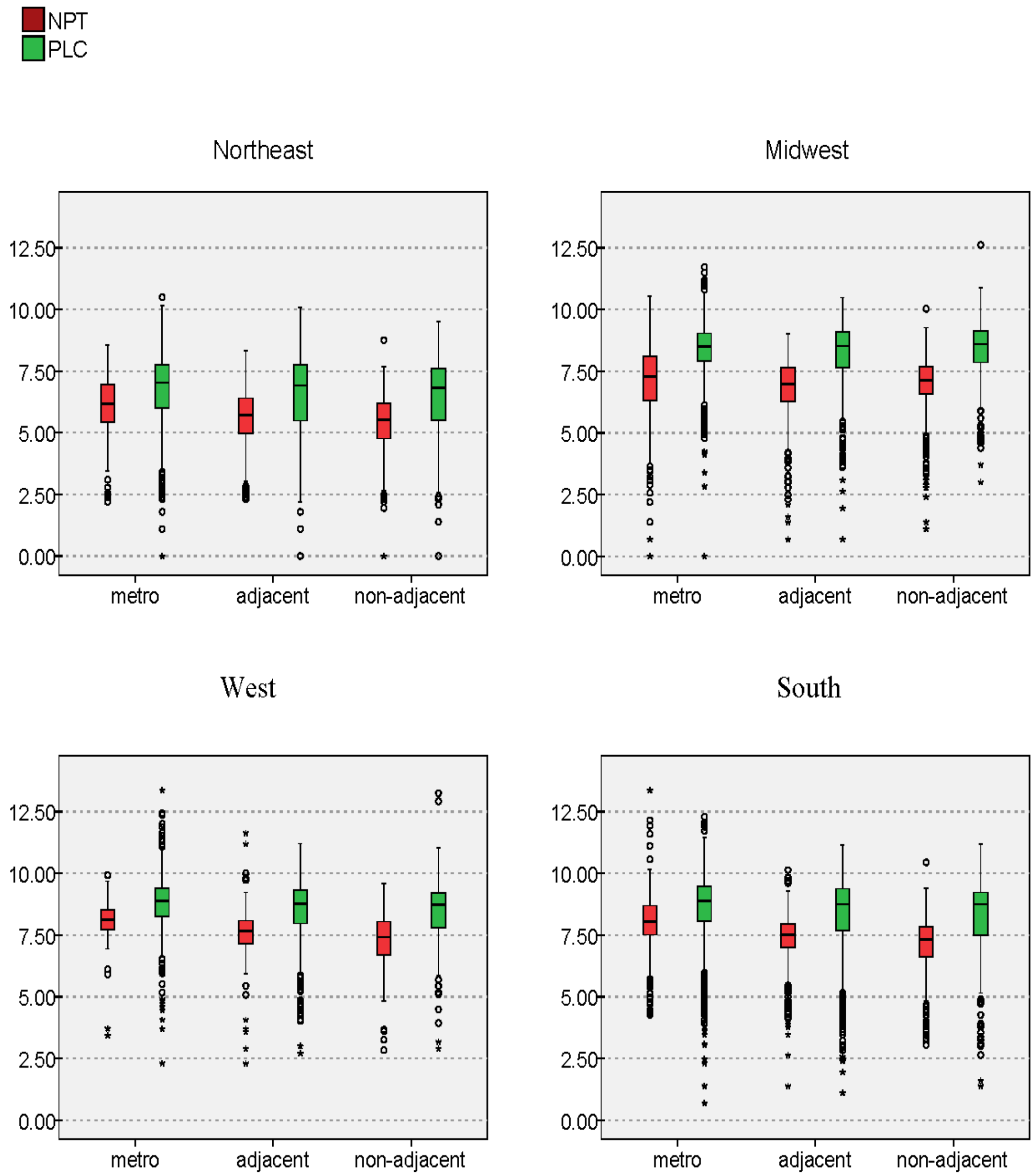
*Metro = Metropolitan; Adjacent = Adjacent Non-Metropolitan; Non-Adjacent = Non-Adjacent Non-Metropolitan

Figure A.15. Boxplots Examining Mean Differences in the Logged Property Crime Rate by U.S. Region and Metropolitan Status, 1990



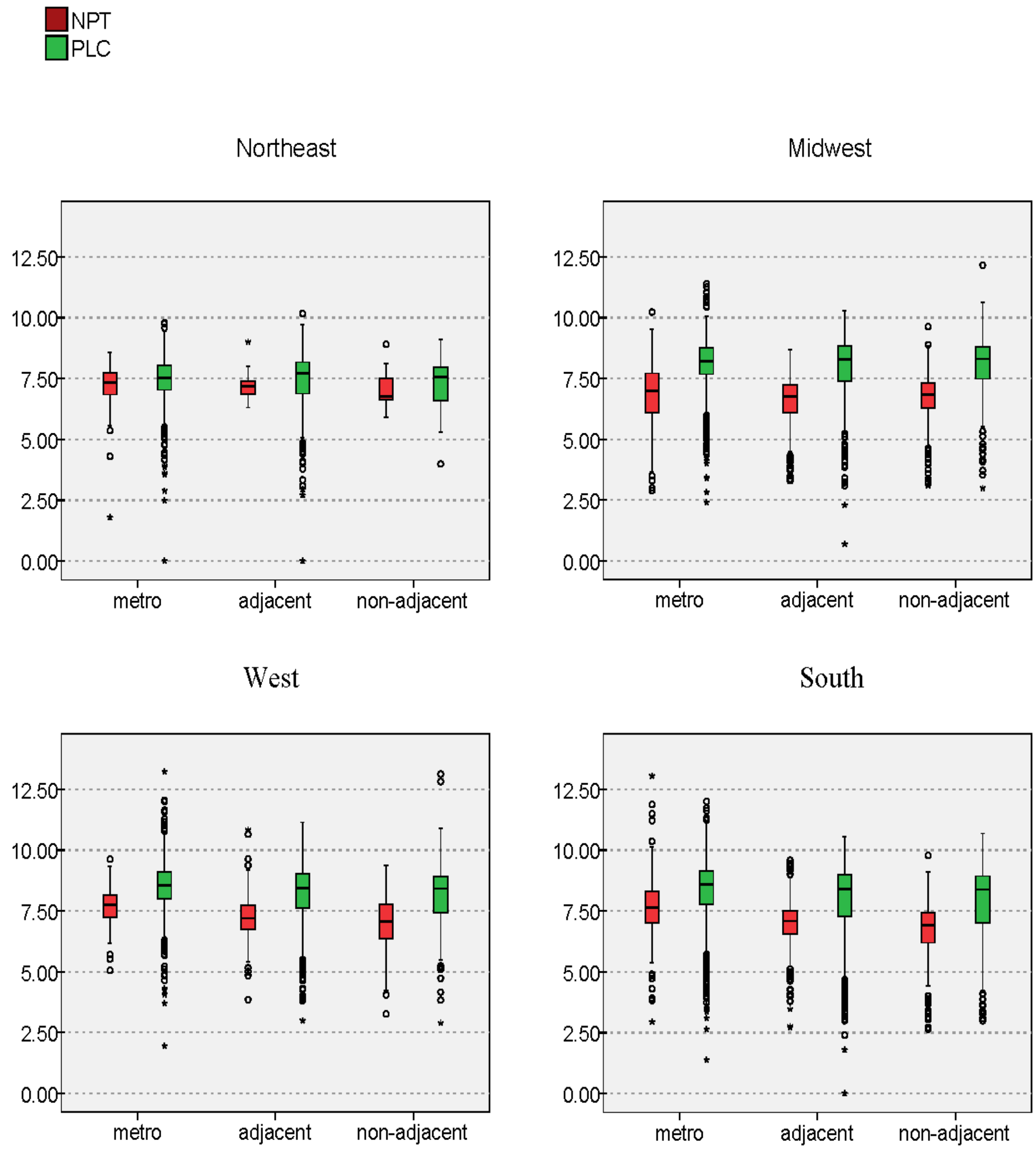
*Metro = Metropolitan; Adjacent = Adjacent Non-Metropolitan; Non-Adjacent = Non-Adjacent Non-Metropolitan

Figure A.16. Boxplots Examining Mean Differences in the Logged Violent Crime Rate by U.S. Region and Metropolitan Status, 1990



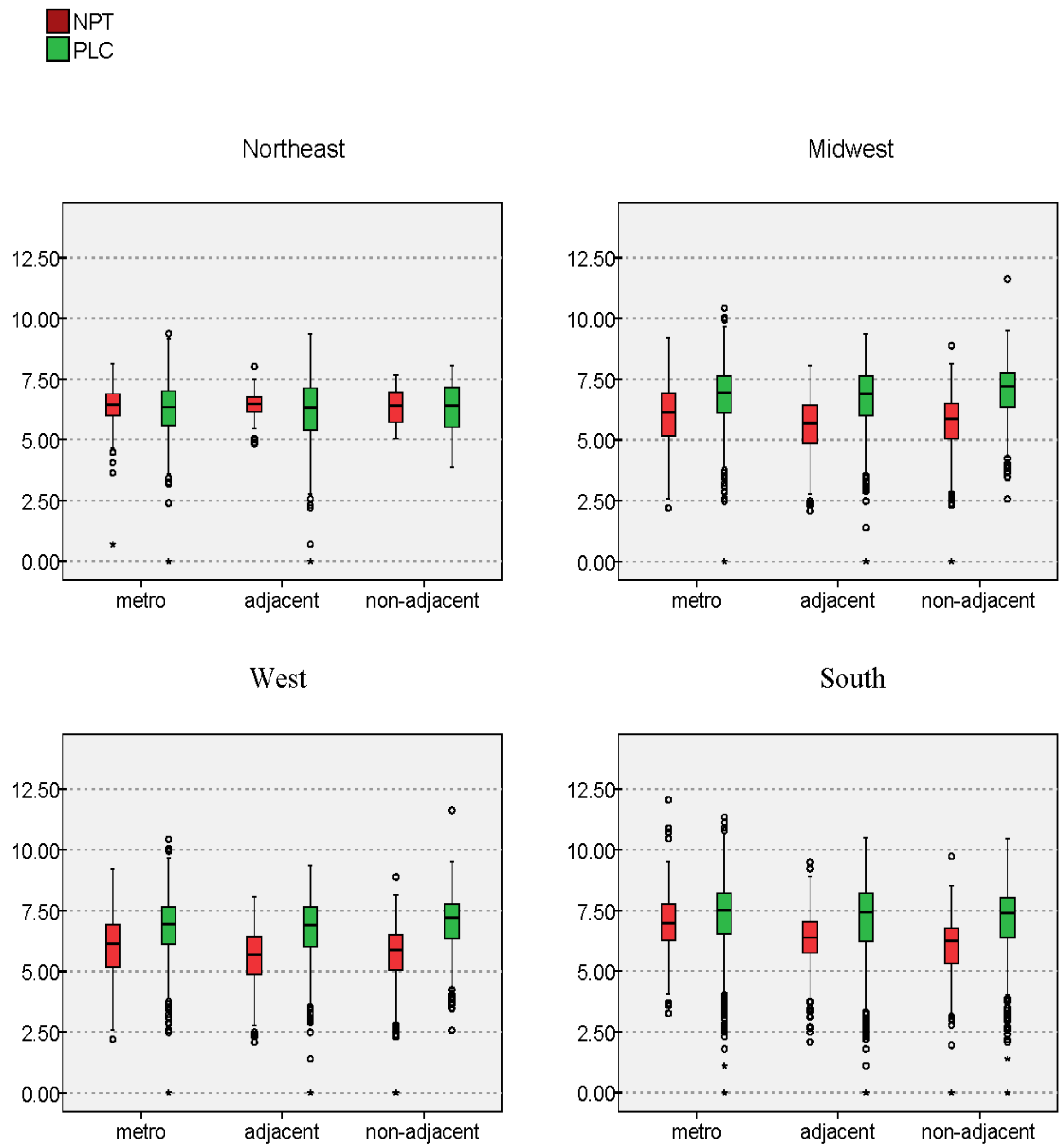
*Metro = Metropolitan; Adjacent = Adjacent Non-Metropolitan; Non-Adjacent = Non-Adjacent Non-Metropolitan

Figure A.17. Boxplots Examining Mean Differences in the Logged Total Crime Rate by U.S. Region and Metropolitan Status, 2000



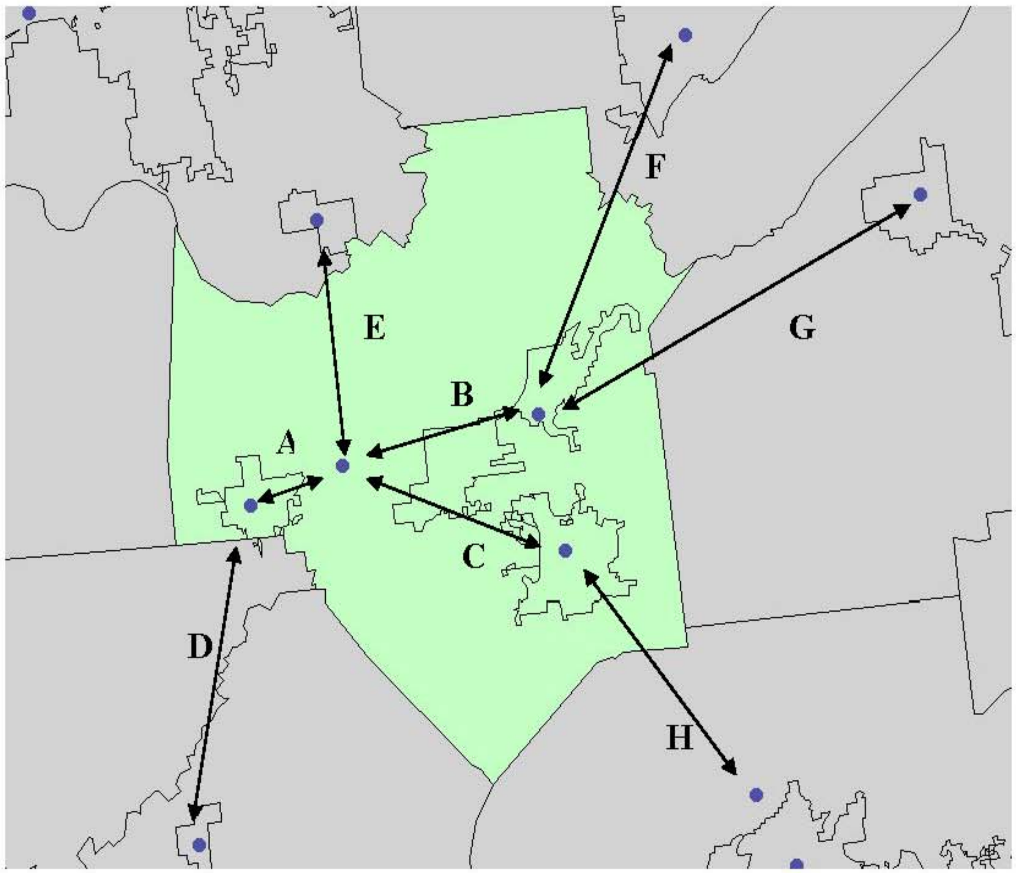
*Metro = Metropolitan; Adjacent = Adjacent Non-Metropolitan; Non-Adjacent = Non-Adjacent Non-Metropolitan

Figure A.18. Boxplots Examining Mean Differences in the Logged Property Crime Rate by U.S. Region and Metropolitan Status, 2000



*Metro = Metropolitan; Adjacent = Adjacent Non-Metropolitan; Non-Adjacent = Non-Adjacent Non-Metropolitan

Figure A.19. Boxplots Examining Mean Differences in the Logged Violent Crime Rate by U.S. Region and Metropolitan Status, 2000



Line Segment	Distance in Miles
Within County	
A	5.4
B	10.9
C	13.1
Between County	
D	17.8
E	15.2
F	21.5
G	24.3
H	16.5

Figure A.20. Example of Nearest Neighbor Definition for Spatial Weight Matrix Using Place-Level Centroids

ENDNOTES

[1] There is an average of 2.75 places within each county with a median of 2.34.

[2] Robinson (1950) introduced the term ecological fallacy as a recognized error in the interpretation of statistical data through the use of inferences about the nature of individuals based aggregate statistics collected for the group to which those individuals belong. This fallacy is related to the idea that all members of the group are alike and can be described using aggregate data.

[3] Dear (1988) was interested in the development of a geographic areas as they relate to the postmodern thinking. Dear believed that as modern cities developed around concentric zones tied closely to primary transportation hubs, newer postmodern cities developed in a much more random pattern tied only to non-physical communication hubs (i.e. telecommunications, etc.)

[4] The intra-place dynamics mentioned by Hawley in *Human Ecology* (1986) is related to the distribution and geographic situation of individuals with a given locale. Over time this distribution changes through modes of evolution such as contraction and expansion, much the same way organisms evolve over time.

[5] Ecological dynamics are directly impacted by the geographic scale of the area of interest (Agnew 1993). Diffusion processes that help disseminate, or are directly concerned with the spatial mobility of a social issue or innovation occurs at many different geographic scales and can be quite different based on the resolution used in the study (Alber et al. 1971). However, as the modern world has become more and more urbanized, and made up of aggregates of individuals (i.e. cities), spatial mobility has taken on a "oozing" dynamic associated with the spread of processes from one area to another (Alber et al. 1971). The globalized patterns brought to light by Yearly (1996) and Wallerstein (1974, 1980, 1989), help to set the framework for place interactions at lower levels of geography. Furthermore, from this point of view it is evident that places tend to perform some sort of function for one another, meaning that the relationship between them can be

viewed as structural (Agnew 1993). It is evident from this section, that the spatial mobility of social processes can be identified and examined at various spatial resolutions (Agnew 1993). Furthermore, each of these resolutions tends to illicit a somewhat different understanding, and potential analytic problems, of the process at hand, whether it is from dilution of variation and activity at a large scale or a misidentification of the process at small scales (Alber et al. 1971). Also, it is evident that the 'diffusion' of social processes tends to be downward in the sense that core areas tend to send information and ideas to periphery areas (Yearly 1996; Wallerstein 1974, 1980, 1989; Agnew 1993; Lightfoot and Martinez 1995).

[6] The differences between all counties for all type-specific crime rates at both points in time were significant at less than the 0.001 level. Of course this is expected based on the large population size. Perhaps more importantly, the amount of variation, as indicated by the eta^2, of each dependent variable by the differences in counties is; Total Crime (1990) = .412, Property Crime (1990) = .407, Violent Crime (1990) = .418, Total Crime (2000) = .429, Property Crime (2000) = .425, Violent Crime (2000) = .435. From these results it is apparent that over 50% of the variation in the dependent variables is not accounted for by the differences between crime rates at the county level, meaning that there is a significant amount of variation remaining within the county.

[7] For further analyses of covariation, each set of independent variables were entered into a principal components analysis by temporal period. The results are similar to the correlation matrix in that there seems to be some shared variation among the sets of determinants. However, this shared variation does not necessarily mean that there will be multicolinearity issues in the predictive analyses and require that colinearity diagnostics be examined as part of the predictive analytic techniques in the following chapter.

[8] Preliminary, and ancillary, analyses were undertaken in order to better understand the general trends of crime from 1990 to 2000 by place-level. In order to accomplish this parallel coordinate plots were created using GGobi and are presented in figures A.7, A.8, and A.9. In relation to the total crime rate (presented in A.7), the non-places decreased as a group over the time period while the place increased. For property crime, neither places nor non-places trended towards an increase of decrease, as a group. Finally in relation to violent crime, the non-places slightly decreased while places did not trend either way as a group.

[9] Tests for mean differences by type-specific crime rates were examined across the newly developed place/non-place geography, metropolitan status, and U.S. Census region independently as well as in a fully-specified repeated measures model. The results of the independent one-way ANOVA analyses are included in the Appendix in table AVII1 and graphically illustrated in figures AVII 6 – AVII16. While focusing on the place-level comparisons, the results show that places, metropolitan counties, the West and South all have higher total, property, and violent crime rates in comparison to their counterparts. Furthermore, there exists extreme variation within each of these categories allowing for the assumption that while certain classifications may in fact have higher group averages, they are likely to vary as they interact with the other classifications. This is examine din the text via the fully specified repeated measures one-way ANOVA approach.

[10] The *k* nearest neighbors approach identifies a theoretically grounded number of meaningful neighbors based on locality centroids and Euclidean distance (Anselin 1995).

[11] For sensitivity purposes, the analyses were run with k=2, 3, and 4. k=3 was ultimately chosen based on the balance between meaningful significant results compared to k=2 and k=4.

[12] When the place-level data was split by the metropolitan status of the larger county, the results show that most of the categorization that can be accounted for by county classification is within the non-adjacent non-metropolitan classification. There is direct support for variations across metropolitan status, further calling for a national scale analysis in order to avoid focusing only on a single metropolitan category for analysis. Across all three metropolitan status categories, the metropolitan counties explained the least amount of between county variations and provided the highest degree of support for the sub-county examination of crime. Metropolitan counties explained with about 33% of the variation being accounted for in 1990 and about 36% being accounted for in 2000. Within adjacent non-metropolitan counties the amount of between case variations rose to about 37% in 1990 and 40% in 2000. Lastly, the non-adjacent non-metropolitan county category explained about 49% in both 1990 and 2000.

[13] A spatial regime refers to any variable which distinguishes between the effects of a given independent variable. Spatially, this is often a level or area of

geographic space in which there is a significant interaction between values of a given variable and the defined neighborhood. In previous analyses of criminal offending at the community-level, the county has been identified as a spatial regime based on a number of different definitions, including both contiguous and nearest neighbors approaches to the definition of neighborhoods. In this analysis there are two spatial regimes, which were identified via a place indicator variable.

[14] Among those counties that were identified as having significant spatial diffusion from places to non-places over the ten year period, 40% were adjacent non-metropolitan counties while metropolitan and non-adjacent non-metropolitan counties both made up 30% of the cases. This large influx of crime in the adjacent counties is likely to be associated with notable in creases and diffusion of crime in the suburbs. The largest percent, 49%, of the cases occurred in the South, with the next highest proportion occurring in the Midwest with 30%. Lastly, 12% took place in the West, while 9% occurred in the northeast.