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EXPLORATORY AND CONFIRMATORY SPATIAL DATA ANALYSIS APPROACHES TO STUDYING THE CORRELATES OF JUVENILE VIOLENT CRIMES

Volume II

Final Report

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VOLUME 2

EXPLORATORY AND CONFIRMATORY SPATIAL DATA ANALYSIS APPROACHES TO STUDYING THE CORRELATES OF JUVENILE VIOLENT CRIMES

In Volume 2, we implement spatial methodologies to study variations in juvenile violent crimes in Virginia. Using county-level data on juvenile violent crime and community risk data, we address the following questions: Do counties with high juvenile violent crime rates tend to cluster together? What risk factors are the primary determinants of juvenile violent crime at the county level?

In Chapter 1, we implement exploratory spatial data analysis methods (ESDA) to study both the local and global patterns of juvenile violent crimes. The focus is on the applications of ESDA as a tool for juvenile justice planning. We specifically examine the applicability of ESDA to monitor spatial and temporal patterns in juvenile violent crimes. In addition, we also explore the applicability of ESDA in identifying "problem counties" that have "atypical" (both spatially and temporally) values of juvenile violent crimes.

In Chapter 2, we implement confirmatory spatial data analysis techniques to study the correlates of juvenile violent crimes. Following Anselin et al. (2000), our study explores both the spatial *interaction (spatial dependence)* and the spatial structure *(spatial heterogeneity)* linking risk factors to juvenile violent crime rates. The focus on spatial heterogeneity allows us to examine if the linkages between risk factors and juvenile violent crimes varies across the various regions on Virginia. In addition, the focus on spatial dependence allows us to examine the county-level diffusive nature of juvenile violent crimes.

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I. Applications of Exploratory Spatial Data Analysis To Monitoring Juvenile Violent Crime Trends

I. APPLICATIONS OF EXPLORATORY SPATIAL DATA ANALYSIS TO MONITORING JUVENILE VIOLENT CRIME TRENDS

1. INTRODUCTION TO THE PROBLEM

In this chapter, we illustrate the applicability of exploratory spatial data analysis (ESDA) methods in juvenile justice planning (Anselin, 1995; 1998). We specifically focus on applications of ESDA to monitoring statewide *levels* and *changes* in juvenile violent crime rates.

We make and support the following two claims:

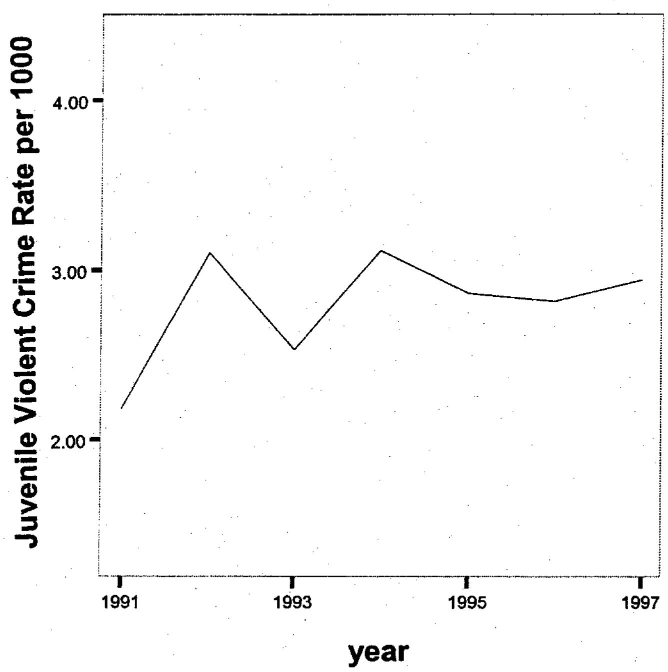
- ESDA can be used by State-level juvenile justice planning staff to monitor spatial and temporal variations in juvenile violent crimes and other key measures
- ESDA can assist in identifying "problem counties/cities" that might be difficult to identify otherwise.

While our specific focus in this chapter is on Virginia, the approach discussed here is generalizable to other States.

Planners in the Virginia Department of Juvenile Justice are charged with responsibility for monitoring changes in key crime trends, including trends in juvenile violent crime rates. Typically, a planner focuses on levels and changes in aggregate measures such as statewide juvenile violent crime rates in monitoring juvenile crimes. Exhibit I-1 describes a graphic that is representative of a fairly typical approach to monitoring trends: it represents statewide levels of temporally smoothed juvenile violent crime that have been aggregated across Virginia's counties and cities between 1991 and 1997. In our experience, there is a very limited focus on spatial variation in juvenile violent crime rates (disaggregated across counties and cities) in Juvenile Justice planning and monitoring activities.

In recent years, there has been a decline in juvenile crime trends (Snyder & Sickmund, 1999)—the decrease has been especially high in some cities and counties. Perhaps quite surprisingly, there has been remarkably little consensus in the research community on the causes of the decline in crime trends (Maltz, 1999; Blumstein & Rosenfeld, 1999). Understanding both the *general* and *local-contextual* factors that can explain such changes in crime trends poses both data collection and methodological challenges. It requires a data collection approach that can track and monitor crime trends, significant events, and local planning processes throughout

EXHIBIT I-1
TEMPORALLY SMOOTHED JUVENILE VIOLENT CRIMES RATES (PER 1000): 1991-1997



the community. Moreover, there is considerable methodological challenge in developing a framework to incorporate both *global* (causal factor works similarly in all regions) and *local-contextual* (causal factor works differently in different regions) explanations of crime (Anselin et al., 2000).

There are at least three problems with an exclusive preoccupation on aggregated statewide statistics: Juvenile crime *trends* might vary dramatically across the different regions of the State; the factors associated with juvenile crimes might vary across different regions—programs designed to meet a statewide need may have little relevance to the needs of specific localities; and, typically, in order to collect information for aggregate analysis, State planners use data from the localities, thereby promoting a unidirectional flow of information *from* the localities *to* the State.

Clearly, there is a role for State-level planners in assisting localities by providing them with analyses of crime trends and social indicators (as that locality compares to the rest of the State). What is needed is a system that tracks crime trends and the "drivers of crime trends";

systematically explores the dynamic context of crime (Sampson, 1993), being sensitive to the fact that explanations of crime can vary across different regions; and facilitates communication between the State and local planners, promoting a system of dynamic feedback. A system of dynamic feedback is essential because localities often resent the imposition of programs from "central office" when they feel "central office" doesn't know what is happening in the localities.

In this chapter, exploratory spatial data analysis methods are implemented using fairly recently developed technological tools (geographical information system (GIS) and spatial statistics software). Central to the argument made in this chapter is that the recent growth in computing power and the development of user-friendly geographical information systems has made it easier for State agencies to implement spatial methods to monitor juvenile crime trends. In this chapter, we specifically focus on the recently developed measures of Local Indicators of Spatial Association (LISA; Anselin, 1995) as a means of understanding local patterns of juvenile violent crimes.

2. THE THEORETICAL AND POLICY RELEVANCE OF SPATIAL AND TEMPORAL PATTERNS OF CRIME

The theoretical insight underlying our proposed project is that the spatial and temporal patterns of crime (both levels and changes) can provide insights into both the *global* and *local-contextual* causes of crime. The goal will eventually be to use ESDA in developing an early warning system on sudden increases in crime rates. Spatial and temporal patterns of crime can often tell a complex story—theory provides a means of "deciphering" the story. As an example, one view of recent declines in crime trends is that declines in crimes are a natural adjustment to past increases in crime (regression to the mean effect; Maltz, 1999). Another view of crime is that that changes in crimes are driven by underlying structural factors such as changes in measures of social disorganization (Sampson, 1993). A third approach views crime as following a diffusion process—in such a view, the declines in the overall crime rates are a result of a spatial process that amplifies small changes in crimes through a "mutually reinforcing" process (Baller et al., 2001). The insight for planning is that explaining the spatial and temporal patterns of crime can help in designing more locally-oriented prevention programs that can respond to local "correlates" of crime more effectively.

From a theoretical viewpoint, the county might be too broad a unit of analysis—as an example, a number of studies that have adopted a social disorganization framework have adopted the census tract as the unit of analysis. The Virginia Department of Juvenile Justice is organized at the local level by counties; therefore, an understanding of the county-level *spatio-temporal* patterns of crime is useful in helping the Department of Juvenile Justice target programs specific to each county. Further, data is more readily available at the county-level. The approach outlined here can be generalized to other "finer" levels without much difficulty.

2.1 Exploratory Spatial Data Analysis Methods: Taking the *Local* Context of Crimes Seriously

Most criminological theories focus on *global* explanations of crime—for the most part, one requires data-driven approaches to better understand the *local* context of juvenile crime. Exploratory spatial data analysis (ESDA) is a subset of exploratory data analysis (EDA) that focuses on the distinguishing characteristics of spatial data—specifically on spatial autocorrelation and spatial heterogeneity (Anselin, 1994, 1998, 1999). The point of departure in ESDA is the same as EDA, namely to use descriptive and graphic statistical tools to discover patterns in data and to suggest hypotheses by *imposing as little prior structure as possible* (Tukey, 1977). More specifically, ESDA is a collection of techniques to describe and visualize spatial distributions, identify atypical locations or spatial outliers, discover patterns of spatial association, clusters or hot spots, and suggest spatial regimes or other forms of spatial heterogeneity (Anselin, 1994, 1998, 1999). Central to this is the notion of spatial autocorrelation or spatial association—the phenomenon where locational similarity (observations in spatial proximity) is matched by value similarity (attribute correlation). (See Cliff & Ord, 1981, and Upton & Fingleton, 1985, for extensive treatments.)

More broadly, the move towards an exploratory spatial data analysis framework is consistent with the expanding role of GIS in social planning (Page, 1993; Hugo, 1993; 1994; Kirby et al., 1998; Plane & Rogerson, 1994). As an example, GIS can inform a rational approach to needs-based planning. Funds for community-based programs such can be allocated based on community needs. The approach discussed here complements the approaches of some other recent NIJ initiatives such as Community Mapping, Planning & Analysis for Safety Strategies (COMPASS) or Strategic Approaches to Community Safety Initiative (SACSI) that implement GIS as a tool for local planning. Unlike the GIS applications in SACSI or COMPASS, we do not collect detailed information on community-level strategies. The strength of our approach is that it has a statewide focus and provides a stronger mechanism to focus on monitoring data.

2.2 Basics of Exploratory Spatial Data Analysis

ESDA builds on methods of exploratory data analysis (Tukey, 1977). As such, ESDA is not necessarily an end in itself, but an organized "search for pattern." One of its goals is to lead us to a rigorous and empirical basis for model specification that can be used in the next stage of the analysis (a spatial multivariate regression model; see Anselin et al., 2000). The key strength of ESDA is its ability to identify the spatial clustering, as well as identification of "anomalous" values (spatial outliers) of juvenile violent crimes.

As an example of the difficulties associated with spatial analysis, consider the following: "The results show that high initial levels of homicide and increases over time in the *spatial proximity* were associated with large losses in total population across 826 census tracts (Morenoff & Sampson, 1997, p. 31; italics added)." One of the difficulties in making such a statement is that we have to define what we mean by spatial proximity. Defining proximity is not a trivial issue and poses considerable methodological challenges. As an example, consider Exhibit I.2. Defining the neighbors of the cell titled "5" is a non-trivial problem and, depending on the criteria, one can arrive at a different definition of "neighbors." As an illustration, if one likens Exhibit I-2 to a chessboard, movement of different chess pieces can lead to different definitions of neighbors. The problem is further compounded by the fact that in most research problems we have both a large number of units of analysis and far more irregular shapes than Exhibit I-2. Given such difficulties, geographical information systems have been especially critical in defining proximity. ESDA methods can implement a variety of proximity measures, including contiguity, distance-based and nearest neighbor measures of proximity (Anselin, 1995).

EXHIBIT I-2
DEFINING A NEIGHBOR

What are the neighbors of 5?

1	2	3
4	5	6
7	8	9

Rook Criteria: 2, 4, 6, 8
Bishop Criteria: 1, 3, 7, 9
Queen Criteria: 1, 2, 3, 4, 6, 7, 8, 9

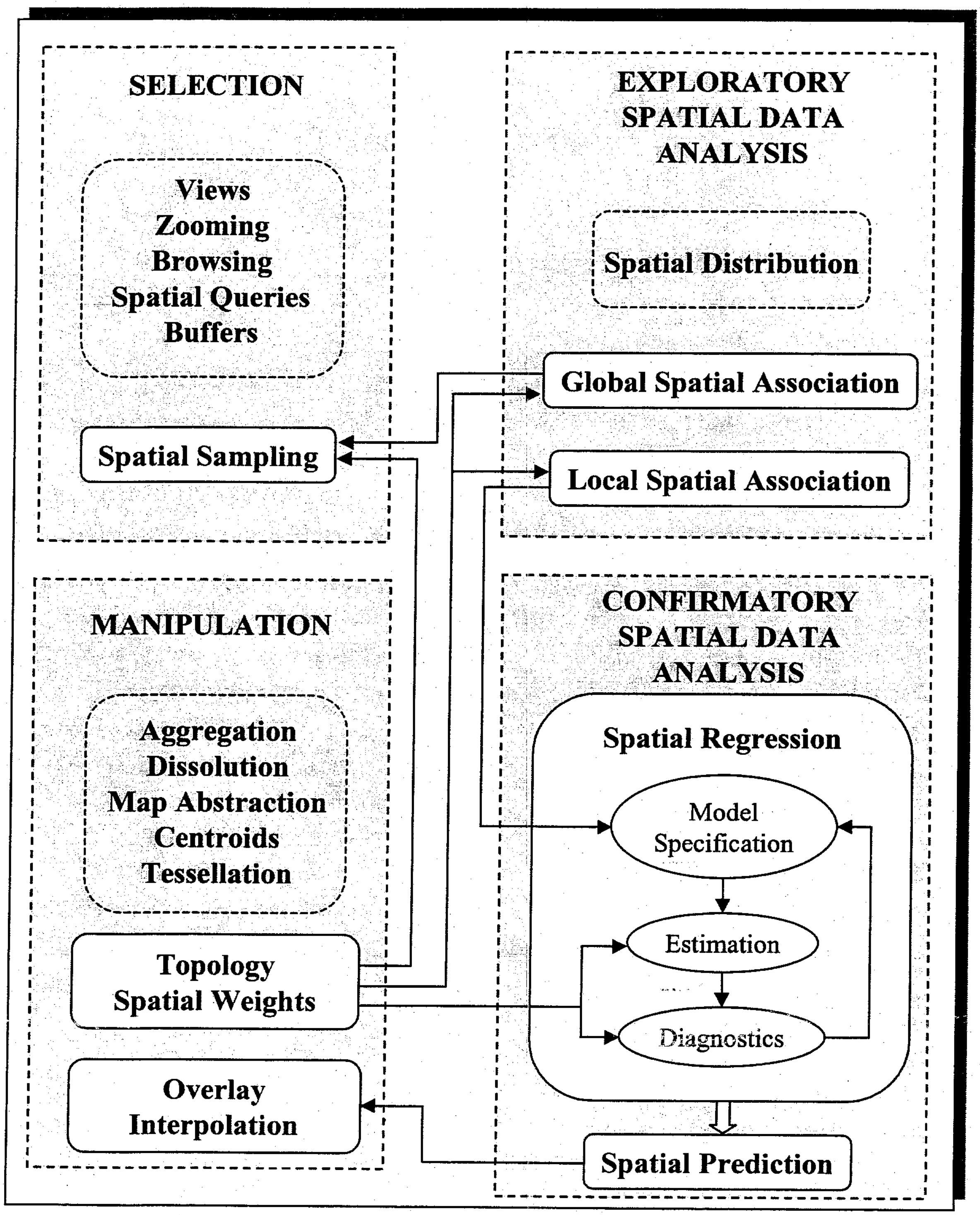
ESDA is implemented through a "coupling" of GIS software[1] with spatial statistics software.[2] The GIS Software is used for defining the spatial weights and for visualization of the results. The spatial statistics software is used for both the exploratory and confirmatory analysis (see Exhibit I-3). In Exhibit I-3, the functionality of the GIS software is described in the left column, and the functionality available in spatial statistics software is described on the right. The key utility of GIS software is in defining the spatial weights. The spatial weights are then imported to the spatial statistics software in which the computation occurs. The results are then moved back to the GIS system for visualization of the results. Alternatively, after the initial ESDA, confirmatory spatial data models are developed in the spatial statistics software.

Both global and local measures of spatial association are used in ESDA. Global measures of association provide an average measure of spatial association across the entire region (a single measure is obtained for the entire data set). Local measures of spatial association provide a measure of association for each county or city—these are implemented

[1] ArcView for Windows in the present implementation.
[2] SpaceStat is one of the very few spatial packages that have implemented the methods described in this chapter.

EXHIBIT I-3

The Spatial Analysis Process



using the so-called Local Indicators of Spatial Association (LISA; Anselin, 1995). As described below, the local measure can be used as a measure of indicators of local spatial clusters and as a diagnostic for local instability.[3]

2.3 ESDA Tools

While multiple tools are available within the ESDA approach, we focus on three tools that will be especially useful in monitoring juvenile crime trends: the Moran scatterplot map, the Moran scatterplot, and the Moran significance map. We also describe the spatial weights matrix and the steps involved in the proposed methodology. Our development of each of these tools is brief—Anselin (1995; 1998) has a far more detailed discussion of these concepts.

The Moran Scatterplot Map

The Moran scatterplot map incorporates information from the individual counties, neighboring counties, and the global average of the outcome measure. A typology of four clusters of counties (note the terms high and low below are defined relative to the global mean—"high" implies higher than the average, "low" implies lower than the average; also note that in this chapter the term counties implies both counties and cities) is developed in the Moran scatterplot map:

- **High-High**—*high value* of outcome measure surrounded by counties that have *high* values of outcome measure (positive association)
- **Low-High**—*low* value of outcome measure surrounded by counties that have *high* values of outcome measure (negative association)
- **Low-Low**—*low* value of outcome measure surrounded by counties that have *low* values of outcome measure (positive association)

[3] The global measure of Moran's I is defined as:

$$I = \sum_i \sum_j w_{ij}.(x_i - \mu).(x_j - \mu) / \sum_i (x_i - \mu)^2$$

where w_{ij} is the row-standardized contiguity matrix, x_i is the measure of juvenile violent crime rate at county I, and x_j is the measure of juvenile violent crime at county j, and μ is the average level of juvenile violent crime rates.

The local measure of Moran's I is defined as:

$$I = \frac{(x_i - \mu)}{\sum (x_i - \mu)^2} \sum_j w_{ij}.(x_j - \mu)$$

- **High-low**—*high* value of outcome measure surrounded by counties that have *low* values of outcome measure (negative association).

In the present application, one has to be cautious in implementing the Moran Scatterplot map. The problem is that a number of counties have a very small population of juveniles; in addition, violent crime is a rare event in a number of counties (especially in the rural counties). As a result, whether or not a county is above or below the mean could vary dramatically from one year to the next with only a minor change in the event count (for example, a county with 100 people and no arrests that goes to 1 arrest moves from a juvenile crime rate of 0 to a rate of 10 (per 1000 population).

The Moran Scatterplot

The Moran scatterplot adds more information to the Moran scatterplot map discussed above. In the Moran scatterplot, the standardized value of the outcome measure (juvenile violent crime rate) is plotted against the weighted average of the standardized juvenile violent crime rates of the neighboring counties. The point's location in the quadrant determines whether it is located in the "high-high," "low-low," "high-low," or "low-low" categories in the Moran scatterplot map. As we illustrate in section 4, the Moran scatterplot is especially useful in identifying outliers.

The Moran Significance Map

The Moran significance map builds on the Moran scatterplot and incorporates information on which of the clusters are statistically significant. Complex permutation methods (Anselin, 1994) are used to conduct the tests of significance. In practice, this is carried out by randomly permuting the observed values over all the locations and calculating the local Moran statistic for each new permutation (Anselin, 1995). The significance of the local Moran statistic is determined by generating a reference distribution using 999 random permutations.

Spatial Weights Matrix

The effects of spatial proximity are operationalized through the spatial weights matrix (see Anselin, 1995; Messner et al., 1999). A number of spatial matrices were considered in the present application.[4] The critical point to note is that the results are conditional on the choice of

[4] These matrices included the rook criteria, queen criteria, distance based contiguity with distance between center less than 35 miles, and four and six nearest neighbors.

the spatial weights matrix. We chose the six nearest neighbors spatial weights matrix. The six neighbors reflect the average for the country: counties in the U.S. have an average of between five to six neighbors. We chose the nearest neighbor criteria in developing the spatial weights matrix because Virginia has a number of city/counties that only have one neighbor (23 counties with only one neighbor). This can significantly disrupt the spatial analysis if we just consider the contiguity criteria. Allowing a fixed number of counties avoids methodological problems that arise when the number of neighboring counties are allowed to vary.[5]

2.4 Steps in Implementing ESDA

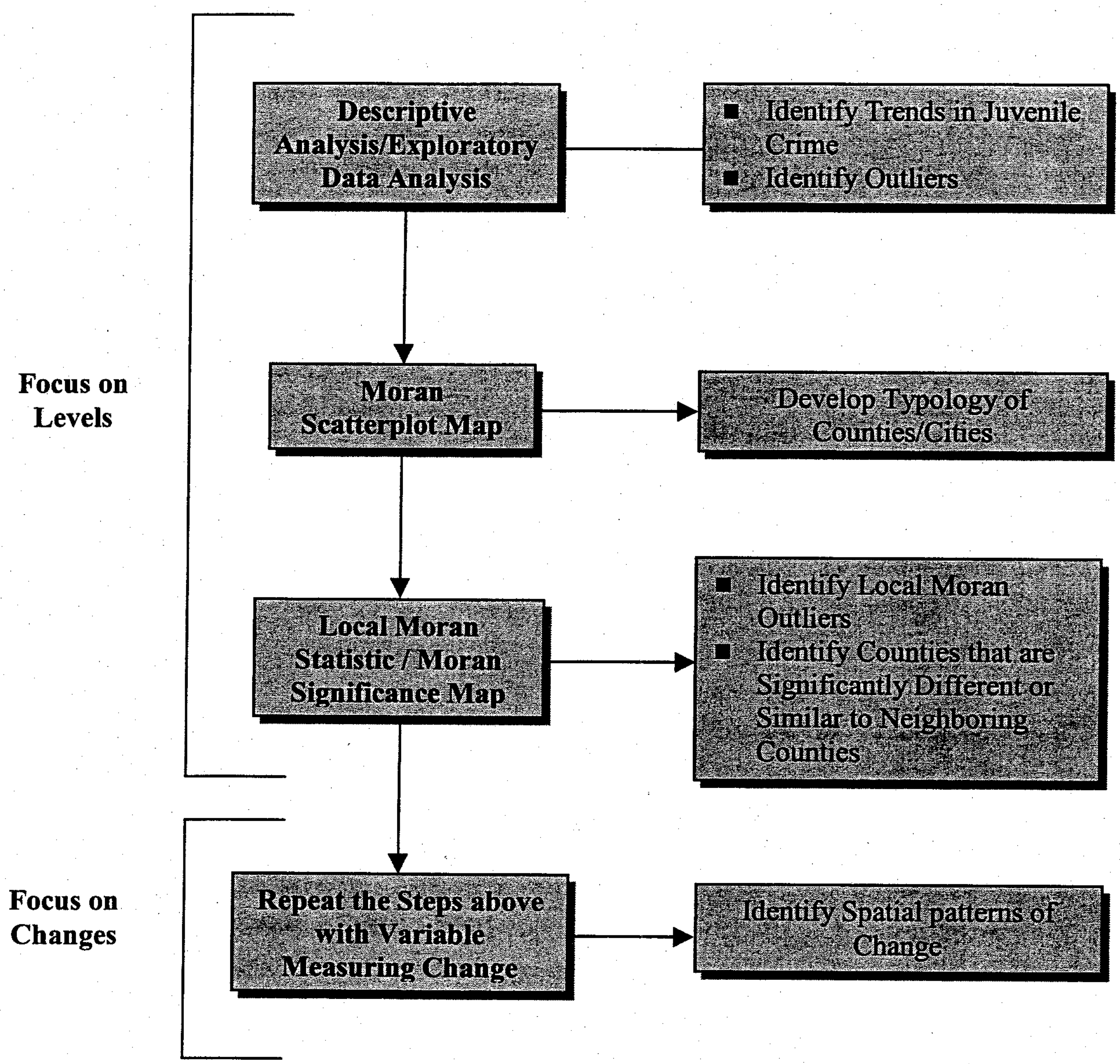
The methodology implemented is described in Exhibit I-4. As a first step, basic descriptive and exploratory methods are utilized to identify mean trends in juvenile violent crimes. In step 2, the Moran scatterplot map is implemented to develop a typology of counties with varying spatial patterns of juvenile violent crimes. In step 3, the Local Moran statistic, the Moran Scatterplot, and the Moran significance map are used to identify spatial clusters of juvenile violent crimes, as well as counties that are significantly different from their neighbors. This process is done both for the *levels* of juvenile violent crime rates and for *changes* in juvenile violent crime rates.

3. MEASURES

We initially explored the exploratory spatial data analysis models with the raw (un-transformed) juvenile violent crime arrest rates. The data was obtained from the Virginia KIDS Count project. Juvenile violent crimes include the total number of arrests of juveniles (less than 18 years old) for murder, forcible rape, robbery, and aggravated assault. These data, based on a calendar year, are collected monthly from contributing law enforcement agencies. This rate is calculated as the number of arrests/population (ages 12-17) multiplied by 1000 (Note: Juvenile Violent Crime rates is per 1000). There were at least two problems with utilizing the raw violent crime rate. The first problem is that, a large number of counties have very small population bases of youth ages 12 to 17 (juvenile population base). Almost 24 percent of the sample had a juvenile population base less than 1,000. The problem with such a small population base is that even a few juvenile violent crimes in this county would result in very high rates. The second problem is that, in a number of counties, violent crime is a rare event. The net result of this was that using the "raw" rates (simple ratios of events over population at risk for a given year) may

[5] The robustness of the results in can be checked by comparing the results generated using both the distance and the nearest neighbor criteria. The difference between the two is that the nearest neighbors criterion "warp" space (no matter how far they are) and the distance criterion assumes isotropy.

EXHIBIT I-4
METHODOLOGY FOR MONITORING SPATIAL PATTERNS IN JUVENILE CRIMES



give a misleading impression of the underlying "true risk" due to the high degree of variance instability. Basically, this means that in small areas the given event count in a year is a very unreliable indicator of the true risk (or true latent measure of violent behavior).[6] Temporal smoothing was used to reduce the variance instability—a 3-year window is used. As an example, the violent crime rate for 1996 was actually a rate based on 1994, 1995 and 1996 data in which the number of events for those three years is divided by the sum of the base population in each year. In a number of cases, this gives a very different result from the single year rate. We similarly calculated the temporally smoothed juvenile violent crime rate for 1997. All the results in this chapter used the temporally smoothed violent crime rates.

4. RESULTS

All of the results presented were implemented using the six nearest neighbor spatial matrix. The significance of the Local Moran statistics was determined by generating a reference distribution of 999 permutations.

4.1 Spatial Patterns of Juvenile Violent Crime Levels

Exhibits I-5 describe the smoothed juvenile violent crime rates in 1996 (in order to conserve space, we have not shown similar exhibits for 1997; henceforth, when we refer to juvenile violent crimes we are actually referring to the smoothed values of juvenile violent crimes). The average level of juvenile violent crime in 1996 is 2.93 and the standard deviation is 3.74. The average value of juvenile crime in 1997 is 2.87 and the standard deviation is 3.53. Exhibits I-5 highlights that the juvenile violent crime rates are higher in the southeastern region (between Norfolk and Richmond) and also towards Northern Virginia near the DC metropolitan region. Exhibits I-6 presents the Box Map with the quartiles and the upper outliers of the juvenile violent crimes in 1996. Exhibits I-5 and I-6 provide some indication of spatial clustering. For example, a number of counties along the western region of the state have lower than average levels of violent crimes. However, inferences from a visual inspection of maps should be made with some caution. "While still extremely popular in applied empirical work, the 'visual inspection' of maps has long been recognized by cartographers as unreliable in terms of detecting clusters and patterns in the data. Human perception is not sufficiently rigorous to assess 'significant' clusters and indeed tends to be biased towards finding patterns, even in spatially random data (Messner et al., 1999)." Another limitation of this and other maps in this chapter is that the crime rates in the cities (which are smaller in areas) are not clearly discernible

[6] As an example, CDC insists on a base population of at least 25,000 before rates can be reported.

EXHIBIT I-5
TEMPORALLY SMOOTHED JUVENILE VIOLENT CRIME: 1996

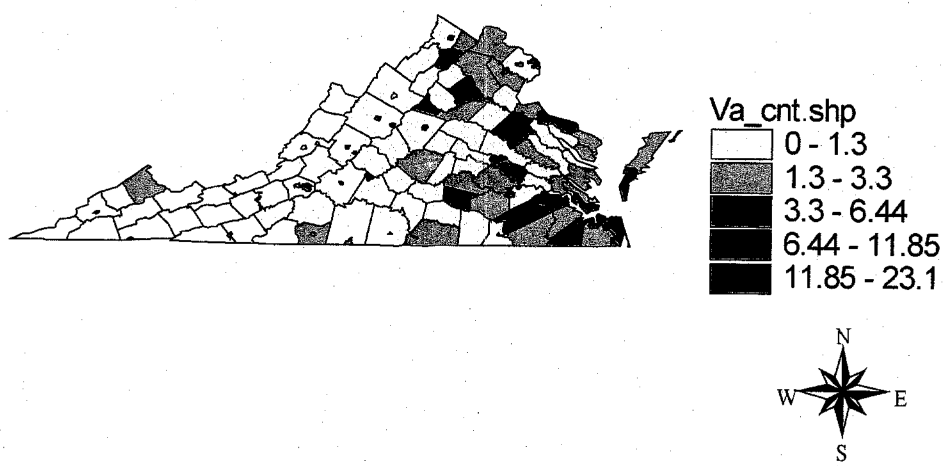
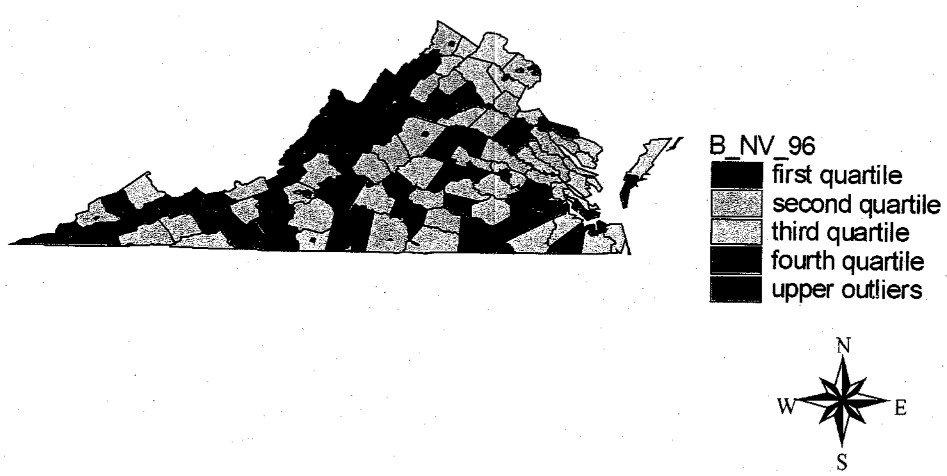


EXHIBIT I-6
BOX MAP PLOT OF TEMPORALLY SMOOTHED JUVENILE VIOLENT CRIME: 1996



from the graph. We turn to the tables discussed below to identify more clearly the spatial patterns in the cities.

Exhibit I-7 reports the results of the global Moran's I for juvenile violent crime rates. The Global Moran's value has an expected value of -1/(n-1)—with 135 counties/cities this value is close to 0 (more precisely -0.007). Value greater than the expected mean imply positive autocorrelation. Values less than the expected mean imply negative autocorrelation. The tests of statistical significance reject evidence of spatial randomness in both the years. The global Moran's I is 0.12 in 1996 and 0.10 in 1997, suggesting positive spatial autocorrelation in both years.

EXHIBIT I-7
GLOBAL MORAN'S I

	I	Z value
Temporally Smoothed Juvenile Violent Crime—1996	0.12	2.81
Temporally Smoothed Juvenile Violent Crime—1997	0.10	2.51

Exhibit I-8 describes the outliers (the 10 highest values) from the exploratory data analysis for 1996 and 1997 juvenile violent crime rates respectively. Emporia City in the southern part of Virginia leads the list in both years. Emporia City also highlights the difficulties of using rates—it has a juvenile population base of 436 and 437 in these years. Even two or three crimes in any one year with such a small population base will result in a high level of crime. However, Emporia has consistently had around 10 juvenile violent crimes in the past five years (resulting in a juvenile violent crime rate upwards of 20 crimes per 1000). Given the consistency of the crimes over time, we can be more assured that a temporal smoothing of the crimes does represent a true rate of juvenile violent crime.

Exhibit I-9 depicts the Moran scatterplot maps for 1996. The typologies of juvenile violent crimes discussed earlier are summarized in these figures. Exhibit I-9 further reinforces the pattern observed in Exhibits I-5 and I-6—the "high" values are primarily concentrated in the northern region and in the areas between Norfolk and Richmond. As discussed earlier, this typology should be interpreted with caution. Given the low population base, the categories may not be too stable because even a single juvenile violent crime can change the categorization of counties.

As discussed above, another way to examine the spatial patterns is the Moran scatterplot (as opposed to the Moran scatterplot map discussed above). In Exhibit I-10, the standardized smoothed juvenile violent crimes in 1996 are plotted against the weighted average of the

EXHIBIT I-8
TOP 10 OUTLINERS—JUVENILE VIOLENT CRIMES 1996/1997

			Locality	Value
Temporally Smoothed Juvenile Violent Crime 1996	Highest	1	Emporia City	23.10
		2	Williamsburge City	15.24
		3	Arlington County	14.51
		4	Richmond City	14.16
		5	Petersburg City	13.68
		6	Winchester City	11.85
		7	Norfolk City	11.02
		8	Hopewell City	10.00
		9	Charlottesville City	9.12
		10	Sussex County	8.97
Temporally Smoothed Juvenile Violent Crime 1997	Highest	1	Emporia City	26.68
		2	Williamsburge City	13.99
		3	Arlington County	12.78
		4	Richmond City	11.24
		5	Petersburg City	10.89
		6	Winchester City	9.89
		7	Norfolk City	9.84
		8	Hopewell City	9.08
		9	Charlottesville City	8.91
		10	Sussex County	8.55

standardized juvenile violent crime rates of the "neighboring" counties. This is an especially effective way of identifying outliers. As an example, consider the selected point (marked in yellow) on the right-hand extreme of the x-axis (lower quadrant)—Emporia City. Emporia City has a high value of juvenile violent crime in 1996, and its six neighboring counties have close to the average level of juvenile violent crimes. A similar pattern is observed in the 1997 graphic (not shown). In both these years, Emporia City has the highest value of juvenile violent crime (see Exhibit I-8), while its six nearest neighbors have an average level of juvenile violent crime. It is this ability to detect such "dramatic contrast" between neighbors that makes spatial analysis especially useful.

The Moran significance map integrates the results of the Moran scatterplot with the permutation tests. Exhibit I-11 describes the results of the Moran significance map in 1996. As is the case with all of the maps in this chapter, the cities are not clearly visible in the map. Exhibits I-12 and I-13 present the cities and counties that have statistically significant local Moran statistics in 1996 and 1997 respectively. A positive spatial association implies that a county with a higher (lower) than average value of juvenile violent crime rate has neighbors that have higher (lower) than average values of juvenile violent crimes. A negative spatial association is implied when a county with a low value of juvenile violent crime (relative to the mean) has neighboring counties with a high value (relative to the mean) of juvenile violent crime

EXHIBIT I-9
MORAN SCATTERPLOT MAP:
TEMPORALLY SMOOTHED JUVENILE VIOLENT CRIME 1996

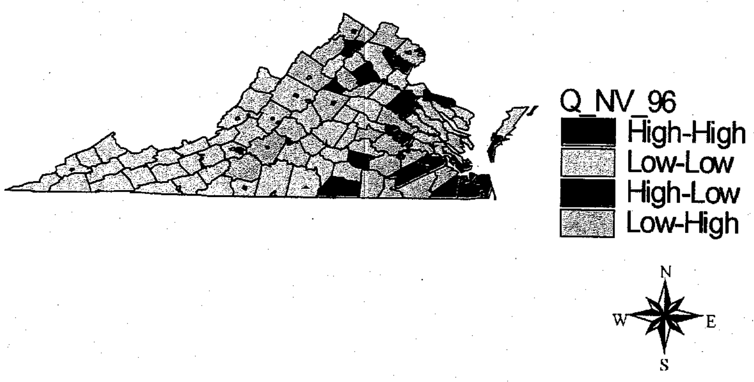


EXHIBIT I-10

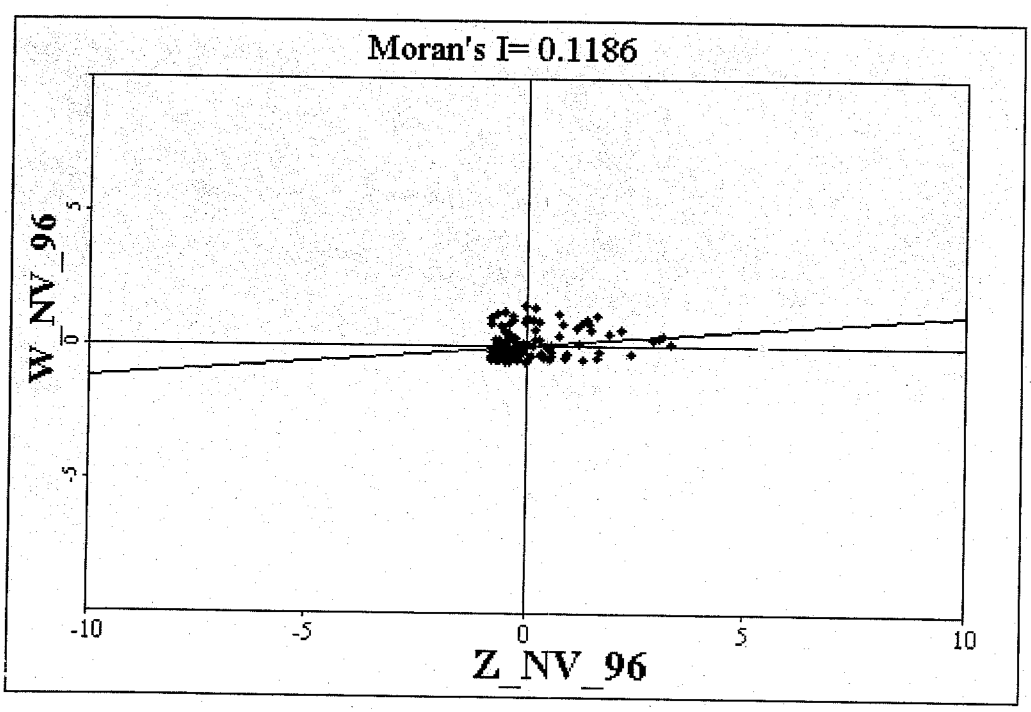
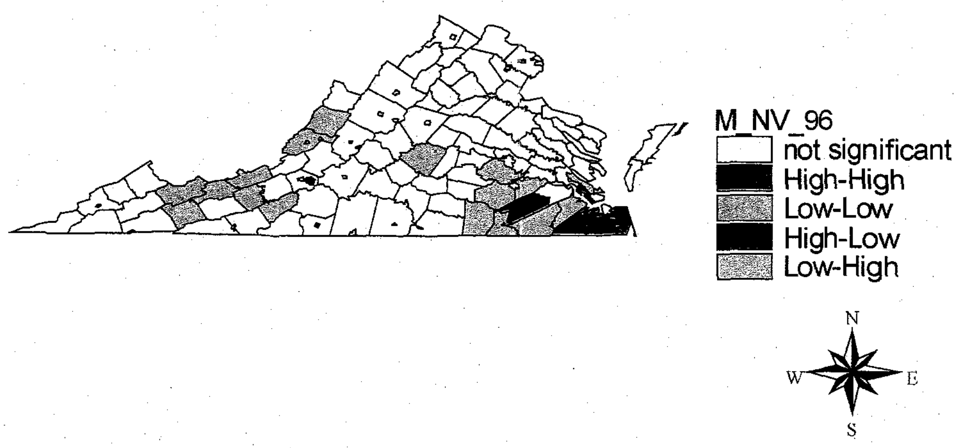


EXHIBIT I-11



and vice versa. We highlight the relevance of the Local Moran statistic by considering two examples of clusters of counties/cities with positive and negative Local Moran statistics respectively. Consider point number 10 in Exhibit I-13, Chesterfield County. It provides an example of a cluster of counties with positive spatial association. Chesterfield County has a violent crime rate of 3.52—this is greater than the mean of 2.87 in 1997. A positive Local Moran statistic is obtained because five of its six neighbors also have juvenile violent crime rates higher than the mean. These include (juvenile violent crimes rates are in parenthesis): Henrico County (3.52), Richmond City (13.99), Hopewell City (7.74), Colonial Heights City (3.98) and Petersburg City (11.24). The only exception is Amelia County (2.27). We return to the Chesterfield County example in section 4.2.

The cluster of counties around Roanoke City (case number 2) provides an example of a negative spatial association. Roanoke City has a high value of temporally smoothed juvenile violent crime (9.08). Its six neighbors include Botetourt County (1.13), Craig County (0.00), Bedford County (0.23), Roanoke County (0.59), Salem City (1.19), Franklin County (1.05). They are all rural counties.

In this example, we have highlighted an example of an ESDA application that focuses on *levels* of juvenile violent crimes. However, in most monitoring applications the interest in assessing *changes* over time. We focus on extending this method to studying change in the next section.

EXHIBIT I-12 STATISTICALLY SIGNIFICANT VALUES OF LOCAL MORAN'S I: 1996					
	Locality	**Local Moran**	**Numbers of Crimes**	**Juvenile Population**	**Temporally Smoothed Juvenile Violent Crime**
1	Sussex County	1.77	3	859	8.97
2	Suffolk City	1.13	24	5,311	8.24
3	Newport News City	1.26	99	14,072	8.08
4	Roanoke City	-.75	57	6,438	7.82
5	Portsmouth City	.98	47	8,444	7.63
6	Fairfax City	.62	17	1,275	6.02
7	Colonial Heights City	.90	4	1,345	5.77
8	Martinsville City	-.28	4	1,216	4.92
9	Falls Church City	.23	4	602	3.95
10	Franklin City	.26	1	752	3.64
11	Virginia Beach City	.15	121	36,157	3.53
12	Chesapeake City	.02	52	17,582	3.00
13	Lexington City	.00	0	337	2.95
14	Galax City	.01	3	465	2.90
15	Chesterfield County	-.03	61	23,031	2.85
16	Dinwiddie County	-.04	8	1,995	2.77
17	Radford City	.11	2	740	2.22
18	Isle of Wight County	-.27	5	2,355	1.89
19	Southhampton County	-.32	2	1,454	1.83
20	Buckingham County	.23	2	1,081	1.56
21	York County	-.32	10	5,792	1.43
22	Giles County	.26	3	1,343	1.24
23	Smyth County	.30	4	2,866	1.17
24	Poquoson City	-.60	3	1,203	1.12
25	Pulaski County	.29	4	2,902	1.04
26	Covington City	.34	0	473	.71
27	Alleghany County	.36	0	1,092	.61
28	Bland County	.35	1	579	.58
29	Tazewell County	.37	3	4,760	.56
30	Prince George County	-.73	0	2,521	.55
31	Floyd County	.40	0	1,049	.32
32	Bath County	.45	0	356	.00
33	Brunswick County	-.60	0	1,402	.00
34	Greensville County	-.80	0	956	.00
Total	N	34	34	34	34

EXHIBIT I-13
STATISTICALLY SIGNIFICANT VALUES OF LOCAL MORAN'S I: 1997

	Locality	Local Moran	Numbers of Crimes	Juvenile Population	Temporally Smoothed Juvenile Violent Crime
1	Newport News City	1.73	144	14,169	9.84
2	Roanoke City	-1.09	73	6,474	9.08
3	Sussex County	1.68	7	869	7.75
4	Lexington City	-.47	5	342	5.92
5	Bristol City	-.36	6	1,268	5.26
6	Suffolk City	.47	10	5,549	4.89
7	Falls Church City	.34	3	619	4.41
8	Galax City	-.25	2	472	4.27
9	Colonial Heights City	.34	7	1,349	3.98
10	Chesterfield County	.22	104	23,442	3.52
11	Franklin City	.11	4	763	3.15
12	Radford City	-.04	4	755	3.12
13	Chesapeake City	.04	51	18,084	3.07
14	Giles County	.10	5	1,346	2.23
15	Isle of Wight County	-.19	5	2,398	2.13
16	York County	-.18	23	5,948	2.07
17	Poquoson City	-.45	3	1,209	1.67
18	Southhampton County	-.55	2	1,471	1.36
19	Smyth County	.32	4	2,875	1.16
20	New Kent County	.28	1	1,076	.96
21	Buchanan County	.30	0	3,256	.91
22	Bland County	.34	0	586	.57
23	Prince George County	-.57	2	2,526	.53
24	Tazewell County	.41	2	4,781	.49
25	Brunswick County	-.78	1	1,419	.24
26	Greensville County	-.97	0	955	.00
Total	N	26	26	26	26

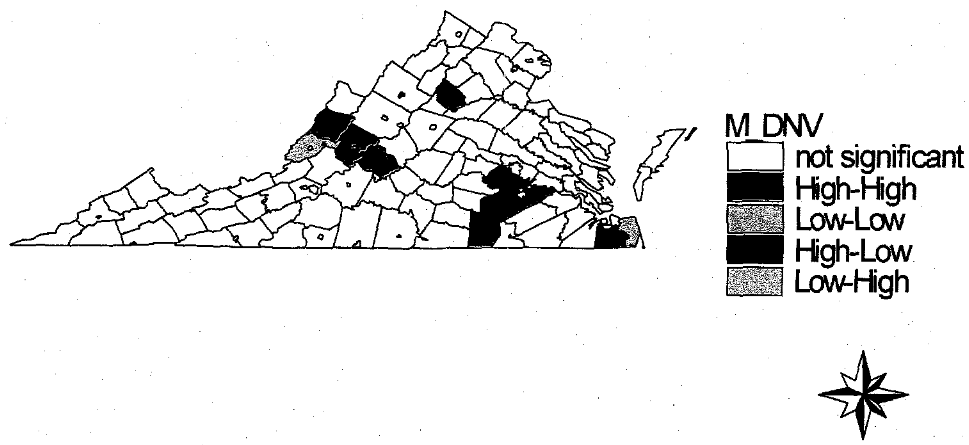
4.2 Change in Juvenile Violent Crime Rates

The above discussion focussed on the levels of juvenile violent crime. We now focus on changes in juvenile violent crime: we illustrate the applicability of this methodology by focussing on the difference between the smoothed values of juvenile violent crimes from 1996 to 1997. Once again, we begin by examining the outliers. Exhibit I-14 describes the 10 counties that have the highest increases and decreases in juvenile violent crime rates between 1996 and 1997. Counties that have had an increase in juvenile crime rates include Emporia City and Roanoke City. Three of Chesterfield County's "neighbors"—Petersburg City, Hopewell City, and Colonial Heights City—are among the counties that have had the maximal decrease.

EXHIBIT I-14 OUTLIERS OF CHANGES IN JUVENILE VIOLENT CRIME RATES			Locality	Value
Changes in Temporally Smoothed Juvenile Violent Crime between 1996 and 1997	Highest	1	Emporia City	3.58
		2	Lexington City	2.97
		3	Northampton County	2.83
		4	Lunenburg County	2.58
		5	Manassas Park City	2.13
		6	Nelson County	1.85
		7	Newport News City	1.76
		8	Mathews County	1.47
		9	Galax City	1.37
		10	Roanoke City	1.26
	Lowest	1	Arlington County	-5.6
		2	Suffolk City	-3.35
		3	Staunton City	-3.10
		4	Williamsburg City	-2.46
		5	Petersburg City	-2.44
		6	Hopewell City	-2.26
		7	Charlottesville City	-2.04
		8	Colonial Heights City	-1.79
		9	Waynesboro City	-1.71
		10	Greene County	-1.69

Exhibit I-15 presents the Moran significance map of the changes in juvenile crime trends. As before, the cities are not clearly discernible in the map—Exhibit I-16 describes the statistically significant Local Moran statistic. In this case, a positive value of the Local Moran statistic implies that a county that has had an increase (decrease) in juvenile violent crime has neighboring counties that have also had an increase (decrease) in juvenile violent crime. A negative value of the Local Moran statistic implies that a county that had a increase (decrease) in juvenile violent crime has neighboring counties that have had a decrease (increase) in juvenile violent crime rates. Consider Virginia Beach City in Exhibit I-16—it has a positive value of the Local Moran statistic. The juvenile violent crime rate in Virginia Beach decreased from 3.53 to 3.23 (this corresponds to a decrease in violent crime from 121 to 88 crimes). Two of its neighbors experienced a substantial decrease in juvenile violent crime rates—Norfolk City (juvenile violent crime rates decreased from 11.02 to 9.98; numbers of cases of juvenile violent crimes decreased from 141 to 132) and Suffolk City (juvenile violent crime rate decreased from 8.24 to 4.89; numbers of crimes decreased from 24 to 10). Its other nearest neighbors experienced more modest changes in crimes—Poquoson City (increase from 1.12 to 1.67), Hampton City (decrease from 7.24 to 7.04), Chesapeake City (increase from 3.00 to 3.07), and Portsmouth City (decrease from 7.63 to 6.48).

EXHIBIT I-15
MORAN SIGNIFICANCE MAP:
CHANGES IN JUVENILE VIOLENT CRIME BETWEEN 1996 AND 1997



Chesterfield County makes the case for the utility of the Local Moran statistic more dramatically—Chesterfield has a negative value of the Local Moran statistic (see Exhibit I-16). While Chesterfield County has had an increase in juvenile violent crime, its neighbors have mostly experienced a decrease in violent crimes. Between 1996 and 1997, Chesterfield County had an increase in violent crime from 2.85 to 3.52 (corresponding to an increase from 61 to 104 crimes). In the same time period, its neighbors had decreases in juvenile violent crime rates—Henrico County (decrease from 3.66 to 3.52), Richmond City (decrease from 14.16 to 13.99), Amelia County (decrease from 2.72 to 2.27), Petersburg City (decrease from 13.68 to 11.24), Hopewell City (decrease from 10.00 to 7.74), and Colonial Heights City (decrease from 5.77 to 3.98). The pattern exhibited by Chesterfield County might be suggestive of a diffusion process—two types of diffusion processes include relocation and expansion. In relocation diffusion, a phenomenon is displaced outward from a point of origin. Similar to relocation diffusion, expansion diffusion refers to a process in which a phenomenon spreads outward from a place of origin, but this center continues to experience the phenomenon. The diffusion process around Chesterfield county might be consistent with relocation diffusion.

In addition to Chesterfield County and Virginia Beach City, Exhibit I-16 lists 13 other clusters of counties with significant values of the Local Moran statistic. A number of the counties might be explained very simply (e.g., Bath County has a positive Local Moran statistic—this is a rural cluster with very small changes in juvenile violent crime rates). Our point is that identification of counties in Exhibit I-16 is useful from a monitoring perspective, *not*

EXHIBIT I-16
STATISTICALLY SIGNIFICANT VALUES OF LOCAL MORAN: CHANGES IN TEMPORALLY SMOOTHED JUVENILE VIOLENT CRIME

	Locality	Local Moran	Numbers of Juvenile Crimes 1996	Numbers of Juvenile Crimes 1997	Juvenile Population 1996	Juvenile Population 1997	Changes in Temporally Smoothed Juvenile Violent Crime Rates
1	Clifton Forge City	.65	0	1	300	300	1.10
2	Harrisonburg City	-.83	4	5	1642	1666	1.01
3	Rockbridge County	.84	0	4	1503	1533	.87
4	Chesterfield County	-.65	61	104	23031	23442	.67
5	Buena Vista City	.49	0	2	507	514	.66
6	Dinwiddie County	-.22	8	7	1995	2005	.24
7	Brunswick County	.18	0	1	1402	1419	.24
8	Chesapeake City	-.10	52	51	17582	18084	.07
9	Bath County	.04	0	0	356	353	.00
10	Madison County	-.03	0	0	1004	1020	.00
11	Amherst County	.04	4	0	2506	2527	-.01
12	Prince George County	-.04	0	2	2521	2526	-.02
13	Virginia Beach City	.15	121	88	36157	36834	-.30
14	Alleghany County	-.36	0	0	1092	1097	-.61
15	Manassas City	-.39	18	4	2623	2712	-.69
Total	N	15	15	15	15	15	15

because every case is significant or important from a planning perspective. On the contrary, we expect that most of the clusters in Exhibit I-16 can be "explained away" with fairly obvious explanations. On the other hand, results in Exhibit I-16 provide a convenient and useful source of information that is not available using the aggregate approach in Exhibit I-1. The important point is that these methods help bring the spatial cluster of "interesting" counties more sharply to the analyst's attention.

Monitoring the simultaneous changes in a large number of counties can be quite overwhelming. Tools are needed to narrow the focus. In our view, the tools discussed in this chapter provide a way to monitor local patterns of crime.

5. DISCUSSION

From a practical policy perspective, we believe the ESDA methodology proposed here will be helpful to the policy and planning group in thinking about monitoring juvenile violent crimes in the following ways. An application of such a methodology could help the Department of Juvenile Justice to be proactive about juvenile violent crime. As an example, Chesterfield County (in Exhibit I-16) provided a potential example of relocation diffusion. Most of its neighbors had seen a decrease in juvenile violent crimes while it experienced an increase. Our proposal to utilize ESDA in juvenile justice planning applications is consistent with the focus of the Office of Juvenile Justice and Delinquency Prevention to think dynamically of the relationship between the planning and evaluation cycles (Wilson & Howell, 1995). Perhaps even more important, such a focus on the local context has the potential of being helpful in improving the relationship between the State and local agencies. For the most part, localities often provide the data, which is then used to produce State-level statistics. With the methods outlined in this chapter, the analysis can be used to better understand the local context of juvenile violent crime. A focus on the local context could provide greater incentives to the localities to share the data on a statewide level.

Most State-level research on juvenile justice has focused on aggregate levels of juvenile violent crimes (aggregated across the State counties and cities). A focus on spatial variations requires more specialized tools, which were not available until recently. In this chapter, we have highlighted a set of tools that can be used by the researcher to understand spatial patterns of crime—the methodology outlined here links geographical information systems software (ArcView for Windows) with spatial econometrics software (SpaceStat). At this time, the level of sophistication required to implement such software is involved, however, as the tools continue to evolve they will become increasingly user-friendly

The utility of ESDA is its ability to focus on the *local context*. We stress that these methods alone do not explain why some regions have spatial clustering or some counties have very high levels of juvenile violent crimes. Some of the explanations might be as simple as low levels of population, or high levels of urbanization. However, the strength of such methodology is that it helps the analyst to focus on a few counties or cities. This is especially the case when there are a large number of counties and cities in the State.

One of the methodological problems we have discussed is the inherent difficulty in working with rates—a number of counties had a very small population base. Even a few events of violent crimes can result in very high values of juvenile violent crime rates. We used temporal smoothing as a solution to the problem. One can think of temporal smoothing as the equivalent of a moving average in a time series, where the peaks and sharp up and downs are replaced by a smooth changing curve. We used the temporally smoothed series to demonstrate the strengths of ESDA. The raw rates could also have been used. However, when comparing statistically significant clusters of counties computed for the raw rates with those for the smoothed rates it is important to keep two things in mind. First, how many of these counties are for "small" areas. Second, how many of these small areas remain outliers after smoothing. If they do, one can be pretty confident that they are "extreme" in some sense. A key qualification to note is that the results of the spatial analysis are conditional on the spatial matrix. In this chapter, we have implemented the six nearest neighbors spatial matrix.

It must be remembered that ESDA is a relatively new field. We have focused on the Moran's I as a measure of local indicators of spatial association (LISA). A number of other measures of LISA are available (Anselin, 1995).

One of the advantages of ESDA is that it forces us to think more deeply about the importance of modeling in understanding changes in juvenile violent crimes. As an example, consider Maltz (1994, p. 457): "We had made do with the assumptions and limitations of standard statistical techniques because, up until very recently, we had no realistic alternatives for analyzing large data sets. To handle them, we have had to employ inexact models whose primary virtue is that they are tractable. But we no longer have to 'model the data.' The increased availability of high-speed, high-capacity computers and excellent data analysis and graphics programs means that we can let the data *speak for themselves* (Maltz, 1994, p. 457)."

In his passionate plea to use innovative statistical and graphical methods and move away from an exclusive preoccupation with global processes, Maltz (1994, p. 457) writes: "We will go much further toward understanding the problems of crime if we relinquish our death-grip on our old beliefs and open ourselves to new methods and paradigms" (Maltz, 1994, p. 457). In our view, ESDA has the potential of making us think more creatively about juvenile justice planning and monitoring.

II. LINKING COMMUNITY HEALTH RISKS TO JUVENILE VIOLENT CRIMES: A SPATIAL APPROACH

II. Linking Community Health Risks to Juvenile Violent Crimes: A Spatial Approach

1. INTRODUCTION

We utilize county-level data from Virginia to study the spatial properties of juvenile violent crimes. Confirmatory spatial techniques are implemented to study the local and global patterns (Anselin, 1995) of juvenile violent crimes. Virginia provides a good setting to examine the local context of juvenile violent crimes: the State contains numerous regions that vary widely in culture, politics, economy, and urbanization. Such variation makes Virginia an ideal place to assess how spatial and social factors relate to juvenile crimes.

The present study contributes to the growing literature on the geography of crime. A focus on the geographical variations of crime can contribute to an understanding of the context, causes, and correlates of crime. A number of statisticians and sociologists have concentrated on geographical variations in crime. In their studies of crime more than 150 years ago, Guerry (1833) and Quetelet (1833) noted the geographical variations in crime. Almost 100 years ago, Redfield (1880) noted that crime rates were higher in the South compared to other regions in the U.S. The social ecological theorists of crime based at the University of Chicago focused on spatial variations in crime (Shaw & McKay, 1942; Park et al., 1925). A number of recent studies informed by a social disorganization perspective have focused on neighborhood level variations in crime (Bursik, 1988; Curry & Spergel, 1988; Sampson & Groves, 1989; Tita et al., 1999).

Utilizing a social disorganization perspective, we examine both the structural and spatial factors associated with the diffusion of juvenile violent crimes. In addition, we also utilize the spatial variations that Virginia provides to determine whether the predictors of juvenile violent crime vary by region. Specifically, for administrative purposes, the Virginia Department of Juvenile Justice divides the State into three administrative regions—the western region, which is primarily rural, the northern, which includes the high density regions around Washington, DC that is primarily suburban, and the eastern region, which includes both rural and high density regions around Norfolk and Virginia Beach. We examine how the predictors of juvenile violent crimes vary across the three regions.

Following Baller et al. (2001), the focus on spatial patterns of juvenile crime allows us to differentiate between structural and subcultural explanations of crime. Structural explanations of crime relate the observed spatial distributions of crime to the hypothesized covariates. Subcultural theories of crime assert that crime cannot be explained entirely by structural factors. As an example, Loftin (1986) has argued for the mutually reinforcing nature of assaultive violence through subcultural dynamics. Space matters in such a view because "proximity drives this subcultural process, as information about violent acts flows through geographically-based social networks and people react to this information. The end result is that serious assaultive violence tends to lead to more violence and in that sense, violence is "analogous to disease," capable of "contagious transmissions" through social and physical space (Loftin, 1986, p. 550)."

The criminological literature has only recently begun to implement methods for studying the complex mechanisms involved in the diffusion of crime (Anselin et al., 2000; Baller et al., 2001; Cohen & Tita, 1999; Messner et al., 1999). Two general mechanisms by which the diffusion process can occur are contagious diffusion and hierarchical diffusion. They can operate either independently or in concert. Contagious diffusion refers to spreading through direct or immediate contact. Criminological examples are located in Messner et al. (1999), Morenoff and Sampson (1997), and Cohen and Tita (1999), where homicides are found to spread from a central location to neighboring areas. As opposed to spreading through contact, hierarchical diffusion refers to spreading through spontaneous imitation or innovation in separate nodes of origin. Cohen and Tita (1999) provide a criminological example, finding evidence that youth homicides increase simultaneously in non-neighboring census tracts during non-peak years. Similarly, the simultaneous origin of crack markets in large cities across the nation contributed to a type of hierarchical diffusion of homicides (Cork, 1999). Recent criminological research has also focused on the structural characteristics that serve as a barrier to diffusion. Messner et al. (1999) demonstrate that affluent communities can act as barriers to the diffusion of homicide from neighboring areas. These tactics of connecting diffusion patterns to location and community characteristics *contextualize* the diffusion process, allowing for a more integrative understanding of complex phenomena like crime. In the present chapter, we examine diffusion of juvenile crimes in Virginia—we do not focus on the type of diffusion—this is the goal of our long-term research program.

The specification of the multivariate models is informed by a social disorganization perspective (Sampson, 1993). This model is grounded in a view of the local community as a complex system of formal and informal social networks rooted in family life and ongoing socialization processes. Structural dimensions of social organization within a community include prevalence and interdependence of social networks and the extent of community supervision of local problems (Sampson & Groves, 1989). In Shaw and McKay's model (1942), an important intervening construct of social disorganization contributing to juvenile delinquency was the ability of a community to supervise and control teenage peer groups. The theory contends that when network density is high, the ability to control delinquency is increased because all network members can potentially react to a participant's behaviors. In addition to informal peer and kinship networks, local participation and connection between community organizations can also reflect community capacity and social organization (Kornhauser, 1978).

Community structural variables that have been used as measures of social organization include poverty, ethnic heterogeneity, family disruption (e.g. divorce or single-parent households), and residential instability. Research has found these measures to be associated with juvenile violent crime rates (Wikstrom & Loeber, 2000; Osgood & Chambers, 2000; Sampson & Groves, 1989).

This study attempts to build on previous work establishing the relevance of spatial patterns and social disorganization to explanations of crime. Towards these ends, we examine the relationships between measures of community health and spatial patterns of juvenile violent crimes across Virginia. Using the social disorganization perspective to frame our approach, we chose to consider the following county-level predictors of juvenile violent crimes: *community health risk* scale that includes county-level measures of prenatal care rates, low birth weight of babies, and infant mortality rates; *teenage risk behavior* scale that includes measures of sexually transmitted disease rates and teenage birth rates; a *school risk measure* operationalized with a single indicator of incidents of students possessing weapons in school; *school performance* scale operationalized by measures of literacy passport tests and high school drop-out rates.

2. WHY COUNTY-LEVEL EFFECTS?

Our choice of counties as the unit of analysis (Baller et al., 2001; Kposowa & Breault, 1993; Messner et al., 1999) is driven by both substantive and practical considerations. The Virginia Department of Juvenile Justice is organized at the local level by counties (and cities). The relationship between county-level risks and juvenile violent crimes would be useful from a policy perspective to the Virginia Department of Juvenile Justice. To our knowledge, there is fairly limited literature on county-level predictors of juvenile violent crime. While diffusion of juvenile violent crime is perhaps more likely at a smaller scale (e.g., neighborhood or census-tract level), data are more readily available for the covariates at the county level. In addition, given our policy focus, we are interested in studying the variation in the juvenile violent crime rates across Virginia. It would be unwieldy to focus on too small a geographical scale for all of Virginia. On the other hand, given the limited knowledge of macro-level predictors of juvenile violent crime, the county itself could also be too small a geographic unit. As discussed in Baller et al. (2001): "If homicide is really a regional phenomenon, slicing the regions of the U.S. into counties will produce spatial autocorrelation, not because of spatial interaction but because counties in the same region experience a common regional cause of homicide ('apparent' contagion). In this case, counties are too small an areal unit."

3. METHODOLOGY

Confirmatory spatial data methods are implemented (Anselin et al., 2000) to study the spatial properties of juvenile violent crime rates.

3.1 The Confirmatory Approach

Following Anselin (1988), our analysis in this chapter makes a distinction between spatial dependence and spatial heterogeneity of juvenile violent crime. Spatial dependence focuses on the relationship between juvenile crimes in proximate counties, after controlling for other covariates. Spatial heterogeneity focuses on the variation in spatial relationships across the geographical regions. Following Anselin (1988), spatial dependence is examined by building spatial lag and spatial error models. As described below, the spatial lag model focuses on the substantively important spatial effects of crime while the spatial error model focuses on spatial effects as "a nuisance which if left unattended would affect inference (Baller et al., 2001)." Spatial heterogeneity is examined by implementing the spatial regimes model (Anselin, 1988).

3.3 Methodological Strategy

We follow the methodology outlined in Baller et al. (2001). A four-step process is used in developing the spatial models to link the covariates to juvenile violent crimes (see Exhibit II-1).

Step 1: Exploratory Spatial Data Analysis Methods to Develop Typology of Counties

This step was discussed in Chapter 1.

Step 2: Identification of the Spatial Process

As a baseline model, an ordinary least squares model is developed to link the county-level risk measures to the juvenile violent crime rates. The primary purpose of building this model is to provide a diagnostic tool for identifying the underlying spatial process. In matrix notation, the baseline model is of the form:

$$y_i = x_i\beta + \varepsilon_i$$

where y_i is the juvenile violent crime rate, x_i are the covariates and ε_i is the residual unexplained by the model.

If there are no spatial patterns in the data, then the residuals should have no spatial patterns:

$$E(\varepsilon_i, \varepsilon_j) = 0$$

A number of diagnostic tests are used to test for any remaining spatial patterns in the residuals. Most of the spatial tests are based on the Lagrange Multiplier principle (Anselin, 1995). In addition, the usual test statistics are computed to assess the presence of heteroskedasticity, non-normality and multicollinearity. The diagnostics help in identifying the form of spatial dependence, specifically, the spatial error or the spatial lag models.

As described earlier, in the spatial error model the spatial patterns are attributable to a clustering of the factors that are not explicitly controlled for in the model. In matrix form, the disturbance component (error process) is modeled as:

$$\varepsilon_i = \lambda W \varepsilon + \mu_i$$

On the other hand, the spatial lag has the form:

$$y = \rho W y + X\beta + u$$

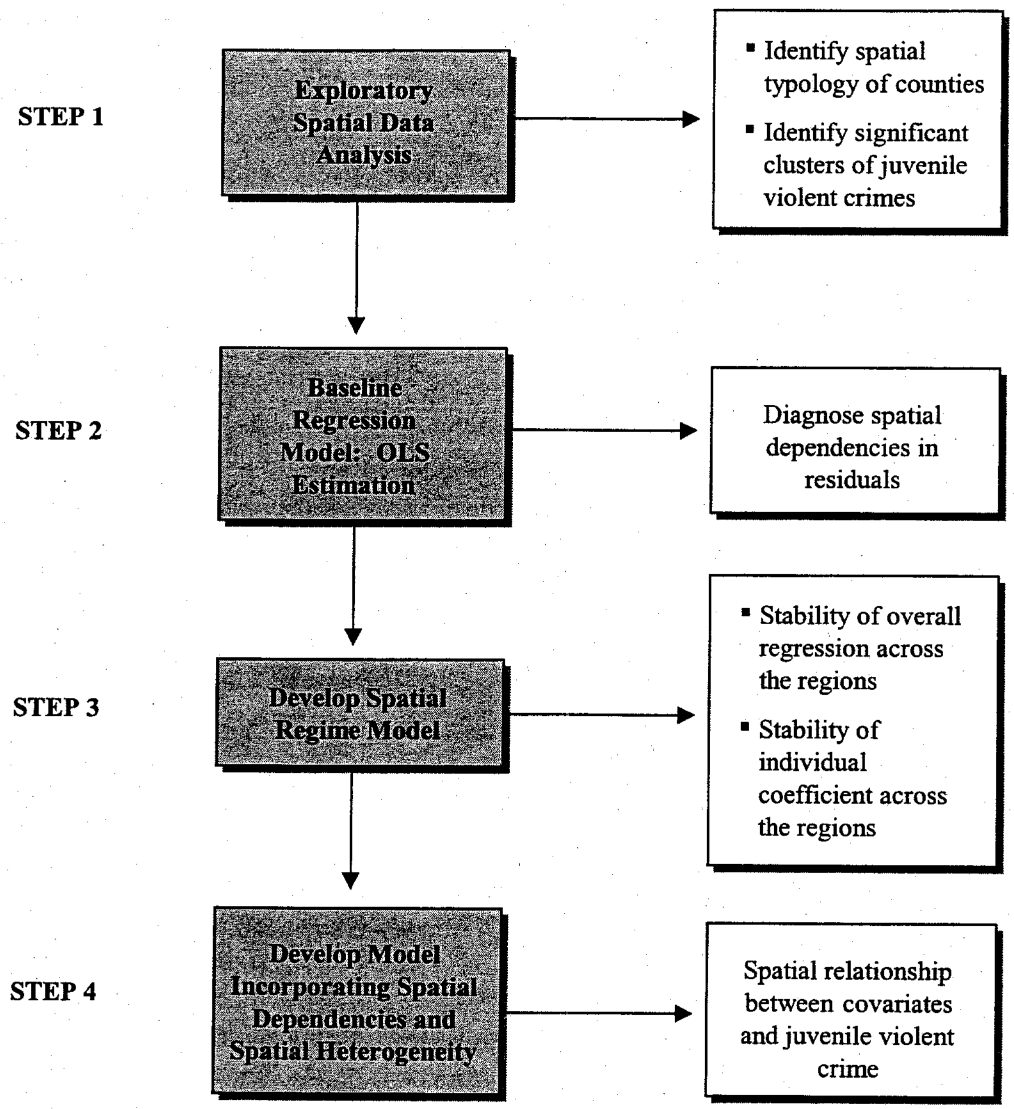
where W is the spatial lag operator (Anselin, 1995) and ρ is the spatial autoregressive parameter.

The spatial lag formulation is used to study the diffusion of crime. One limitation of this operationalization of diffusion is that it is static. This is potentially problematic because diffusion of crime is a dynamic phenomenon:

> Any diffusion or contagion process requires "vectors of transmission," i.e., identifiable mechanisms through which events in a given place at a given time influence events in another place at another time. Consequently, a diffusion process is by necessity dynamic, whereas the spatial lag model is static. The hypothesized mechanisms involve normative and attitudinal adaptations, which are proxied in the model thorough the spatial multiplier. However, their spatial lag model, as such, is not able to discover these mechanisms, only to properly represent them in their cross-sectional equilibrium state (Baller et al., 2000).

It is important to note that while a battery of spatial diagnostic tools are available to study the forms of spatial dependence (spatial lag vs. spatial error models), the diagnosis step does not definitively differentiate between spatial heterogeneity and spatial dependence.

EXHIBIT II-1
STEPS IN BUILDING THE SPATIAL REGRESSION MODEL



Step 3: Testing for Spatial Heterogeneity

A spatial regime model is implemented to test for spatial heterogeneity across Virginia's regions by allowing the structural covariates and the residual covariance to vary across the regions. The spatial regime model (Anselin, 1988) tests for the stability of the overall regression as well as the stability of individual coefficients across the regions. In addition, the residuals are examined for spatial dependence.

Step 4: Developing Models Incorporating Spatial Dependence and Spatial Heterogeneity

When step 3 indicates that separate models need to be developed for each region (based on the overall spatial chow test), steps 1 and 2 are repeated in order to develop the model for each of the regions separately. If there is no support for developing separate models for the regions, the results of the spatial diagnostics tests in step 2 are used in estimating the overall model, incorporating the spatial dependencies.

4. MEASURES

As discussed in chapter 1, the data are from the Virginia Kids Count project (Galano et al., 1998). Juvenile violent crime rate is the dependent measure --As discussed in chapter 1 temporal smoothing was used to reduce the variance instability of the dependent measure. A 3-year window is used: As an example, the violent crime rate for 1997 was actually a rate based on 1995, 1996 and 1997 data in which the events for those three years is divided by the sum of the base population in each year. All the results in this chapter used the temporally smoothed violent crime rates.[1]

Independent Measures

Temporal smoothing procedures similar to those described above were used to calculate all of the rate measures described in this section. The principal component scales described below were developed on the temporally smoothed measures.

[1] Another strategy is to change the reference base for the computation of the rate. Instead of using only the county itself, one uses a moving window that includes the county and its immediate neighbors. For example, one could take each county and its six nearest neighbors, sum the events for those seven units and divide them by the total population at risk for the seven units. Alternatively, one could use a distance measure (e.g. 35 miles) to define the neighbors. This procedure is called "spatial smoothing" in SpaceStat.

Community Health Risk Measure. Principal component analysis was used to develop a community health risks scale comprised of the following measures: prenatal care rates, percentage of low birth weight babies, and infant mortality rates. Prenatal care rates are calculated as the number of pregnant females receiving early care divided by the total number of live births. Low birth weight is calculated as the number of low weight births (under 2500 grams) divided by the total number of live births, based on a calendar year. Infant mortality is calculated as the number of deaths of children under 1 year of age divided by the total number of live births, based on a calendar year. The scale explained close to 58 percent of the variance of the original measures. The factor loadings of the original measures on the underlying scale are as follows (in parenthesis): prenatal care rates (-0.76), percentage of low birth weight babies (0.82), and infant mortality rates (0.70). Our choice of this measure is informed by a social disorganization perspective. Infant mortality is linked to teen pregnancy, smoking and alcohol abuse. Access to prenatal care can help identify and prevent some of these conditions (U.S. Department of Health and Human Services, 2000). In addition to its association with infant mortality, lack of prenatal care is linked to lower birth weight and poorer developmental outcomes. In a socially disorganized community with weaker social networks and less capacity for social control, access to and awareness of prevention measures is likely to be decreased. Furthermore, several studies have found an association between prenatal and perinatal complications and later delinquency or criminal behavior (Kandel et al., 1989; Kandel & Mednick, 1991; Raine et al., 1994). A high score on this scale indicates higher levels of community health risks.

Risky Behavior among Teenagers. This construct was operationalized using a principal components scale comprised of measures of teenage birth rates and STD rates among teenagers. Teenage birth rates are based on a calendar year and calculated as the number of live births to females under age 17, divided by the total population of females aged 15 to 17, and multiplied by 1000. STD rates are based on a calendar year and calculated as the number of reported STD cases divided by the number of 12- to 17-year-olds and multiplied by 1000. The scale explained close to 83 percent of the variance in the original measures. The factor loadings of the measures were as follows (in parenthesis): teenage birth rates (0.91) and STD rate (0.91). The National Campaign to Prevent Teen Pregnancy (1998) reports that children of teen mothers are twice as likely to be abused and neglected and that boys born to teen mothers are three times more likely to end up in jail. Teenage mothers are less likely to receive prenatal care and more likely to have complications during pregnancy, leading to poor developmental outcomes for their children (Child Welfare League of America, 1998). Teenage risky behavior may also be reflective of social disorganization; teens with strong attachments to their parents are less likely to have sex, linking teenage behavior to informal and formal involvement in the community (Moore, et al., 1998; Blum & Rinehard, 1997). A high score on this scale is indicative of higher levels of risk behavior among teenagers.

Risk of Violence in School was operationalized through a measure of incident rates of weapons in school. This measure is based on the fiscal year and was calculated as the number of instances students were found to have weapons on school property, divided by average daily school membership and multiplied by 1000.

School Performance Scale. Principal component analysis was used to develop a school performance scale that comprised the following measures—literacy passport tests and high school drop-out rates. The literacy passport tests assess mastery of 6th grade-level skills in mathematics, reading, and writing. The data are based on a fiscal year and measure the percentage of students who passed all three literacy passport tests. High school drop-out rates are based on the fiscal year and represent the percentage of 9th to 12th graders who dropped out of school. Many studies have found connections between poor school performance, leaving school at a young age, and delinquency (Huizinga & Jakob-Chien, 1998; Hagan & McCarthy, 1997; Hawkins et al., 1998; Simons et al., 1991; Thornberry et.al., 1984; Schorr, 1998). The scale explained close to 67 percent of the variance in the original measures. Factor loadings of the original measures on the principal components scale are: Literacy passport tests (0.82) and high school drop-out rates (-0.82). Higher values on this scale correspond to superior county-level academic performance.

Family Risks was operationalized through a single measure of out-of-wedlock births. This measure is based on the calendar year and was calculated as the number of births to women who had not been married to the father during the preceding 10 months, divided by the total number of births and multiplied by 100.

Resource Deprivation and Affluence Component. Following Land et al. (1990), principal component analysis was used to develop a scale with the following measures—rates of children under age 18 living in poverty,[2] percentage black, and fiscal stress level.[3] The fiscal stress level is obtained from the Virginia Commission on Local Government's annual fiscal stress index of Virginia's cities and counties. Variables used in determining the index include per capita revenue capacity, revenue effort, and median adjusted gross income. Factor loading included (in parenthesis)—rates of children under age 18 living in poverty (0.90), percentage black (0.65), and fiscal stress level (0.86). Localities with higher levels of resource deprivation

[2] These rates were only available for 1993. The data from 1993 were used to calculate these rates.
[3] The Land et al., study (1990) included median family income (logged), a Gini index of family income, percent black, percent of families below poverty, and percent of female-headed families.

are less likely to have the resources to support children and families. In addition, they are more likely to have higher deep-end costs (jails and foster care), detracting from their ability to afford front-end interventions. A high score on this scale is indicative of communities with higher levels of resource deprivation.

Population Structure Component. Non-linear principal component analysis[4] was used to develop a scale comprising the following measures: logged population size from 1997, logged population density from 1997, and whether the jurisdiction was a city or a county. This measure can be predictive of juvenile offending, as previous studies have discovered relationships between population size, population density, and delinquency (Sampson, 1983; Laub, 1983). The scale accounted for about 62.1 percent of the variation in the measures—factor loadings were as follows—logged population (0.43), logged population density (0.97), and city (0.86).

In addition, for some of the models developed in this chapter, we also included dummy measures for region.

5. RESULTS

The results of the exploratory spatial analysis are discussed in Chapter 1.

Exhibit II-2 describes the means of the dependent and independent measures by region. Exhibit II-3 presents the ANOVA results for equality of means across the three regions. From Exhibit II-3, there exist statistically significant differences across the regions at the 0.05 level for *juvenile violent crime rates, community health risk measures, unmarried mothers,* and the *resource deprivation* measure. Exhibit II-4 presents bivariate correlation between the predictor measures and juvenile violent crime rates for the complete sample. From Exhibit II-4, all of the predictors are significantly associated with juvenile violent crimes—all in the expected directions. Tables II-5(a), II-5(b) and II-5(c) study the bivariate correlation between the independent measures and the juvenile violent crime by the region. Given the small sample size of counties and cities within a region, we discuss the within-region results at the 0.10 level of significance. While *community health risks*, *teenage risks*, *unmarried mothers*, *resource deprivation* and the *population dimension* are significantly associated with juvenile violent crime in all regions, *weapons in school* and *school performance* have a differential impact across the regions.

[4] Nonlinear principal component analysis was used instead of linear principal component analysis as the measures were at mixed levels of measurement—the population and population measures are numeric measures, while the city measure is nominal.

Exhibit II-6 depicts the results of the ordinary least squares (OLS) regression for the complete sample. The OLS model explains close to about 61 percent of the variation in juvenile violent crime rates. Statistically significant relationships were observed between *community health risks*, *teenage risks*, *population dimension* and *juvenile violent crime rates*. Higher values of *community health risks*, *teenage risks* and the *population dimension* are associated with higher levels of juvenile violent crimes. The residuals are then examined for spatial patterns. The diagnostics do not provide any support for spatial dependence; however, the spatial diagnostics do indicate problems with non-normality and heteroskedasticity.

The results of the diagnostics are checked by examining the spatial lag model and the spatial errors model for the complete model (see Exhibit II.7 and Exhibit II.8 respectively). Maximum likelihood methods were used to estimate the models presented in Exhibits II-7 and II-8. Both these tables essentially replicate the results from Exhibit II-6. Neither the spatially lagged term in Exhibit II-7, nor the spatial effects terms in Exhibit II-8 are significant.

Exhibit II-9 presents the results of the spatial regime model, which allows the coefficients to vary across the regions—the variance of juvenile violent crime explained rises from 61 percent to close to 74 percent. The spatial Chow test for the overall regression provides support for a difference between the regressions across the regions—rejecting the null hypothesis of coefficient stability. The tests for the stability of individual coefficients indicate differences in the following coefficients across the regions: *community health risk*, *teenage risks*, and *resource deprivation scale*. This suggests that these structural characteristics exert different effects across regions. In addition, it also suggests that the regional variations may not be completely accounted for by including dummies for a region. Once again, there are no significant spatial patterns of dependence in the residuals. However, problems still persist with normality, multicollinearity, and heteroskesdasticity. Based on this result, we examine the regional spatial processes by developing a baseline ordinary least squares model for each of the regions.

Given the small sample size for the regression model of the regions, the power is low. We describe the results at the 0.10 level of significance.

Exhibit II-10 describes the results of the ordinary least squares for the western region. The model explains close to 60 percent of the variation in juvenile violent crime for the western region. Statistically significant predictors include *teenage risks* and the *population dimension*. Higher values of *teenage risks* and the *population dimension* are associated with higher values of juvenile violent crime rates. Examinations of the residuals do not indicate spatial patterns of dependence. Problems with heteroskesdasticity still persist.

The OLS model of juvenile violent crime rates in the northern region in Exhibit II-11 explains close to 74 percent of the variation in juvenile violent crime rates. Statistically significant predictors of juvenile violent crime include *community health risk, academic performance* and the *population dimension*. Higher values of community health risks and the population dimension are associated with higher levels of juvenile violent crimes. Lower values of academic performance are associated with higher values of juvenile violent crimes. The OLS residuals do not indicate a strong pattern of spatial dependence. Once again, there are problems in multicollinearity and heteroskesdasticity with the model.

Exhibit II-12 describes the OLS model for the eastern region. The model explains close to 73 percent of the variation in juvenile violent crime rates. At the 0.10 level, predictors of juvenile violent crimes include the *community health risks*, *teenage risks*, *resource deprivation* and the *population dimension*. Higher values of *community risks*, *teenage risks* and the *population dimension* are associated with higher values of juvenile violent crimes. Higher values of *resource deprivation* are associated with lower values of juvenile violent crimes—this result is counter-intuitive and perhaps a result of multicollinearity problems in the model. The bivariate correlations in Exhibit II-5(c) further support the assessment that the negative coefficient between *resource deprivation* and juvenile violent crimes is perhaps the result of multicollinearity problem (the bivariate correlation between resource deprivation and juvenile violent crime is 0.443 ($p < 0.005$)). Given the small sample size in the eastern region (n=37), we urge caution in the interpretation of the results. Problems still persist with multicollinearity, non-normality and heteroskesdasticity. The OLS residuals once again do not indicate any strong spatial patterns of dependence.

6. DISCUSSION

In this chapter, we have implemented confirmatory spatial methods to understand the local and global context of crime. Specifically, we implement the spatial regimes model to study the variations in the linkages between the correlates of juvenile violent crimes across the three regions of Virginia. In addition, we also implement the spatial lag model to study the county-level diffusion of juvenile violent crime.

Diffusion is a dynamic phenomenon, and the multivariate, confirmatory framework in this article focused on diffusion in a "comparative statics" framework. We found no support for the diffusion of juvenile violent crime rates. Our analysis contrasts somewhat with Baller et al.'s (2001) investigation of diffusion of homicide rates in U.S. counties—they found a spatial lagged effect (diffusion effect) to explain the homicide rates in southern counties in1960, 1970, 1980, and 1990. One of their significant findings was that the spatial lagged effect reduced over time.

A diffusion effect was also found for non-southern counties in 1960. While our analysis focuses only on a single State, the results do suggest that the diffusion properties of juvenile violent crime rates might differ from adult homicide rates. For future research, it would be interesting to examine the diffusion properties of juvenile violent crimes at a much smaller scale than the county.

A second feature of our analysis is our examination of the relationship between juvenile violent crime and several measures of county-level risks. Two substantively meaningful predictors included the measures of community health risks and teenage risks. In two of the three regions, increases in *community health risks* and *teenage risks* are associated with high levels of juvenile violent crime rates. As we understand these measures to be indicative of social disorganization, these results provide support for the linkage between social disorganization and juvenile violent crime. However, some of our other measures do not present as strong an association. Unlike Baller et al. (2001), we do not find a strong relationship between resource deprivation and juvenile violent crime rates. We also found very limited support for linkage between weapons in school and teenage violent crime rates. Predictably, higher values on the population dimension were associated with higher values of juvenile violent crimes.

Perhaps the most important result was the existence of spatial regimes across the three regions of Virginia. We observed differences across the regions in the linkages between community health risks, teenage risks, and resource deprivation and juvenile violent crimes. In contrast to the other regions, school performance was a predictor of crime in the northern region and teen risks were not. While community health risks are a predictor in both the northern and eastern regions, the association is not significant in the western region. In addition, a significant linkage between resource deprivation and juvenile violent crime was only found in the eastern region. These are potentially important results because they indicate a need for juvenile delinquency prevention strategies that are more tailored to the respective regions. In addition, the linkages between community risks and juvenile violent crimes also encourage a broader perspective on juvenile violent crimes. This provides support for contextualizing explanations of juvenile violent crime, and for viewing it as a public health problem.

The analysis conducted in this chapter also had a few methodological limitations: Juvenile violent crimes tend to be rare events—as an example, a number of counties in our study did not have any juvenile violent crimes in the period of our study. Modeling such low base rate phenomena is inherently problematic. Most of the spatial regression models developed in this chapter had problems with non-normality and heteroskesdasticity. These problems do not weaken the key results of this chapter: (i) The findings of the absence of diffusion at the county-level; (ii) support for the possibility of differing explanations of juvenile violent crime across the three administrative regions of Virginia. On the other hand, as a result of the problems with non-normality and heteroskesdasticity, the coefficients and the hypothesis tests in the various models should be interpreted with caution.

In a recent work, Anselin et al. (2000) write: "the promise of using spatial data and analysis still remains to be demonstrated and depends on the nature of the relationship between crime and place (Anselin et al., 2000, p. 213)." Our work provides mixed support for this contention.

EXHIBIT II-2
MEANS OF OUTCOME MEASURE BY REGION

	Region			
	Western	Northern	Eastern	Total
Juvenile Violent Crimes	1.75	3.07	4.40	2.87
Community Health Risks Measure	-.11	-.17	.36	.00
Teenage Risks	-.23	.11	.24	.00
Weapons in School	2.32	2.75	2.35	2.46
School Performance	.10	.15	-.32	.00
Unmarried Mothers	31.00	29.75	37.81	32.49
Resource Deprivation	.12	-.57	.45	.00
Population dimension	-.17	.16	.10	.00

EXHIBIT II-3
ANOVA TABLE OF DEPENDENT AND INDEPENDENT MEASURES BY REGION

		Sum of Squares	df	Mean Square	F	Sig.
Juvenile Violent Crime	Between Groups	161.26	2	80.63	7.06	.00
	Within Groups	1,519.52	133	11.42		
	Total	1,680.78	135			
Community Health Risks Measure	Between Groups	6.77	2	3.38	3.51	.03
	Within Groups	127.23	132	.96		
	Total	134.00	134			
Teenage Risks	Between Groups	5.71	2	2.85	2.94	.06
	Within Groups	128.29	132	.97		
	Total	134.00	134			
Weapons in School	Between Groups	4.89	2	2.45	.83	.44
	Within Groups	389.70	132	2.95		
	Total	394.59	134			
School Performance	Between Groups	5.23	2	2.61	2.68	.07
	Within Groups	128.77	132	.98		
	Total	134.00	134			
Unmarried Mothers	Between Groups	1,482.62	2	741.31	5.75	.00
	Within Groups	17,029.03	132	129.01		
	Total	18,511.65	134			
Resource Deprivation	Between Groups	21.42	2	10.71	12.56	.00
	Within Groups	112.58	132	.85		
	Total	134.00	134			
Population dimension	Between Groups	3.07	2	1.54	1.54	.22
	Within Groups	132.93	133	1.00		
	Total	136.00	135			

EXHIBIT II-4
CORRELATIONS BETWEEN JUVENILE VIOLENT CRIME AND PREDICTORS—COMPLETE SAMPLE

	Juvenile Violent Crime Pearson Correlation	Sig. (2-tailed)
Community Health Risks Measure	.493	.000
Teenage Risks	.676	.000
Weapons in School	.257	.003
School Performance	-.300	.000
Unmarried Mothers	.456	.000
Resource Deprivation	.408	.000
Population dimension	.546	.000

EXHIBIT II-5(a) **CORRELATIONS BETWEEN JUVENILE VIOLENT CRIME AND PREDICTORS—WESTERN REGION**		
	Pearson Correlation	**Sig. (2-tailed)**
Community Health Risks Measure	.239	.074
Teenage Risks	.690	.000
Weapons in School	.014	.918
School Performance	-.169	.208
Unmarried Mothers	.505	.000
Resource Deprivation	.462	.000
Population dimension	.654	.000

A Region = Western

EXHIBIT II-5(b) **CORRELATIONS BETWEEN JUVENILE VIOLENT CRIME AND PREDICTORS—NORTHERN REGION**		
	Pearson Correlation	**Sig. (2-tailed)**
Community Health Risks Measure	.435	.004
Teenage Risks	.634	.000
Weapons in School	.530	.000
School Performance	-.336	.031
Unmarried Mothers	.326	.037
Resource Deprivation	.443	.004
Population dimension	.703	.000

A Region = Northern

EXHIBIT II-5(C) **CORRELATIONS BETWEEN JUVENILE VIOLENT CRIME AND PREDICTORS—EASTERN REGION**		
	Pearson Correlation	**Sig. (2-tailed)**
Community Health Risks Measure	.601	.000
Teenage Risks	.710	.000
Weapons in School	.252	.132
School Performance	-.303	.068
Unmarried Mothers	.476	.003
Resource Deprivation	.440	.006
Population dimension	.449	.005

A Region = Eastern

EXHIBIT II-6
ORDINARY LEAST SQUARES ESTIMATION FOR THE ENTIRE SAMPLE

R^2 0.61
AIC 620.89

Variable	Coeff	S.D.	T-Value	Prob
Constant	5.92	1.51	3.91	0.00
Western Region	-1.43	0.50	-2.84	0.00
Northern Region	-1.57	0.62	-2.54	0.01
Community Health Risks Measure	1.18	0.32	3.73	0.00
Teenage Risks	1.97	0.40	4.97	0.00
Weapons in School	0.01	0.13	0.05	0.96
School Performance	-0.16	0.27	-0.58	0.57
Unmarried Mothers	-0.06	0.04	-1.45	0.15
Resource Deprivation	-0.63	0.49	-1.28	0.20
Population Dimension	1.09	0.24	4.51	0.00

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 20.49

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	1420.05	0.00

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Koenker-Bassett test	9	82.17	0.00

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHTS MATRIX NN6_6 (row-standardized weights)

Test	MI/DF	Value	Prob
Moran's I (error)	-0.02	0.16	0.87
Lagrange Multiplier (error)	1	0.23	0.63
Robust LM (error)	1	0.00	0.97
Lagrange Multiplier (lag)	1	0.42	0.52
Robust LM (lag)	1	0.19	0.66
Lagrange Multiplier (SARMA)	2	0.42	0.81

EXHIBIT II-7
SPATIAL LAG MODEL-MAXIMUM LIKELIHOOD ESTIMATION

R^2 0.61
AIC 622.39

Variable	Coeff	S.D.	Z-Value	Prob
Spatial Lag Effect	-0.09	0.12	-0.75	0.45
Constant	6.34	1.54	4.10	0.00
Western Region	-1.69	0.58	-2.92	0.00
Northern Region	-1.75	0.63	-2.76	0.01
Community Health Risks Measure	1.17	0.30	3.87	0.00
Teenage Risks	1.94	0.38	5.07	0.00
Weapons in School	0.01	0.13	0.07	0.94
School Performance	-0.17	0.26	-0.64	0.52
Unmarried Mothers	-0.06	0.04	-1.51	0.13
Resource Deprivation	-0.64	0.47	-1.35	0.18
Population Dimension	1.14	0.24	4.73	0.00

EXHIBIT II-8
SPATIAL ERROR MODEL-MAXIMUM LIKELIHOOD ESTIMATION

R^2 0.60
AIC 618.59

Variable	Coeff	S.D.	Z-Value	Prob
Constant	5.99	1.42	4.21	0.00
Western Region	-1.48	0.45	-3.27	0.00
Northern Region	-1.59	0.57	-2.80	0.00
Community Health Risks Measure	1.16	0.30	3.85	0.00
Teenage Risks	1.96	0.38	5.10	0.00
Weapons in School	0.01	0.13	0.09	0.93
School Performance	-0.14	0.26	-0.56	0.58
Unmarried Mothers	-0.06	0.04	-1.59	0.11
Resource Deprivation	-0.58	0.46	-1.27	0.20
Population Dimension	1.09	0.23	4.79	0.00
Spatial Error Effects	-0.09	0.16	-0.58	0.56

EXHIBIT II-9
DIAGNOSTICS FOR SPATIAL REGIME REGRESSION FOR THE ENTIRE SAMPLE

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER 33.26
TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	108.52	0.00

TEST ON STRUCTURAL INSTABILITY FOR 3 REGIMES DEFINED BY REGION

TEST	DF	VALUE	PROB
Chow test	16 112	4.54	0.00

STABILITY OF INDIVIDUAL COEFFICIENTS

Test	DF	Value	Prob
Constant	2 112	0.39	0.67
Community Health Risks Measure	2 112	7.54	0.00
Teenage Risks	2 112	8.88	0.00
Weapons in School	2 112	1.66	0.19
School Performance	2 112	1.02	0.36
Unmarried Mothers	2 112	0.00	0.99
Resource Deprivation	2 112	5.14	0.01
Population Dimension	2 112	2.11	0.12

DIAGNOSTICS FOR HETEROSKEDASTICITY
LINEAR SPECIFICATION USING VARIABLES
CONSTANT REGIO_2 REGIO_3

TEST	DF	VALUE	PROB
Koenker-Bassett test	2	10.76	0.00

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHTS MATRIX NN6_6 (row-standardized weights)

Test	MI/DF	Value	Prob
Moran's I (error)	-0.03	0.28	0.78
Lagrange Multiplier (error)	1	0.49	0.48
Robust LM (error)	1	1.46	0.23
Lagrange Multiplier (lag)	1	0.00	0.96
Robust LM (lag)	1	0.97	0.32
Lagrange Multiplier (SARMA)	2	1.46	0.48

EXHIBIT II-10
ORDINARY LEAST SQUARES ESTIMATION FOR THE WESTERN REGION

R^2 0.60
AIC 203.65

Variable	COEFF	S.D.	T-Value	Prob
Constant	3.52	1.36	2.58	0.01
Community Health Risks Measure	0.03	0.29	0.10	0.92
Teenage Risks	1.62	0.52	3.12	0.00
Weapons in School	0.15	0.13	1.14	0.26
School Performance	-0.06	0.25	-0.23	0.82
Unmarried Mothers	-0.05	0.04	-1.15	0.26
Resource Deprivation	0.22	0.38	0.57	0.57
Population Dimension	0.88	0.25	3.47	0.00

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 19.85
TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	0.34	0.84

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	7	20.79	0.00

SPECIFICATION ROBUST TEST

TEST	DF	VALUE	PROB
White	35	40.88	0.23

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHTS MATRIX NN6_6_1 (not row-standardized)

Test	MI/DF	Value	Prob
Moran's I (error)	-0.09	-0.78	0.44
Lagrange Multiplier (error)	1	1.49	0.22
Robust LM (error)	1	0.08	0.78
Lagrange Multiplier (lag)	1	1.71	0.19
Robust LM (lag)	1	0.30	0.58
Lagrange Multiplier (SARMA)	2	1.79	0.41

EXHIBIT II-11
ORDINARY LEAST SQUARES ESTIMATION FOR NORTHERN REGION

R^2 0.74
AIC 168.50

Variable	Coeff	S.D.	T-Value	Prob
Constant	4.33	3.21	1.35	0.19
Community Health Risks Measure	1.31	0.55	2.38	0.02
Teen Risks	0.09	0.68	0.14	0.89
Weapons in School	0.15	0.21	0.73	0.47
School Performance	-0.92	0.46	-2.03	0.05
Unmarried Mothers	-0.06	0.08	-0.69	0.50
Resource Deprivation	-0.08	1.05	-0.08	0.94
Population Dimension	2.07	0.44	4.72	0.00

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 27.24
TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	10.75	0.00

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Koenker-Bassett test	7	9.12	0.24

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHTS MATRIX NN6_6_2 (not row-standardized)

Test	MI/DF	Value	Prob
Moran's I (error)	-0.06	-0.15	0.88
Lagrange Multiplier (error)	1	0.49	0.48
Robust LM (error)	1	1.44	0.23
Lagrange Multiplier (lag)	1	0.01	0.91
Robust LM (lag)	1	0.96	0.33
Lagrange Multiplier (SARMA)	2	1.45	0.48

EXHIBIT II-12
ORDINARY LEAST SQUARES ESTIMATION FOR THE EASTERN REGION

R^2 0.73
AIC 191.28

Variable	Coeff	S.D.	T-Value	Prob
Constant	6.64	4.27	1.55	0.13
Community Health Risks Measure	2.63	0.75	3.51	0.00
Teen Risks	3.97	0.83	4.79	0.00
Weapons in School	-0.52	0.50	-1.04	0.31
School Performance	-0.09	0.72	-0.13	0.90
Unmarried Mothers	-0.04	0.11	-0.40	0.69
Resource Deprivation	-2.96	1.24	-2.39	0.02
Population Dimension	0.95	0.51	1.88	0.07

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER 27.86
TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	10.93	0.00

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Koenker-Bassett test	7	18.72	0.01

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHTS MATRIX NN6_6_3 (not row-standardized)

Test	MI/DF	Value	Prob
Moran's I (error)	-0.01	0.70	0.49
Lagrange Multiplier (error)	1	0.00	0.95
Robust LM (error)	1	0.61	0.43
Lagrange Multiplier (lag)	1	0.56	0.45
Robust LM (lag)	1	1.16	0.28
Lagrange Multiplier (SARMA)	2	1.17	0.56

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