2007

Examining Spatiotemporal Change in Neighborhood Crime Using Social Disorganization as a Theoretical Framework: A 10-Year Analysis of Homicide in the City of Richmond, VA

Suleyman Demirci
Virginia Commonwealth University

EXAMINING SPATIOTEMPORAL CHANGE IN NEIGHBORHOOD CRIME USING SOCIAL DISORGANIZATION AS A THEORETICAL FRAMEWORK: A 10-YEAR ANALYSIS OF HOMICIDE IN THE CITY OF RICHMOND, VA

A Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

by

SULEYMAN DEMIRCI
B.A., Middle East Technical University, Ankara/Turkey, 1995
M.S., University of North Texas, Denton/Texas, 2001

Director: LAURA J. MORIARTY, PH.D.
PROFESSOR AND VICE PROVOST FOR
ACADEMIC AND FACULTY AFFAIRS

Virginia Commonwealth University
Richmond, Virginia
May 2007

Acknowledgments

It has been a long journey to reach this point as I am persuading my PhD studies. I have experienced every elements of psychology during this journey. This journey has continuously reflected many trade offs between encouragements and challenges. Whenever I need something and/or someone, there have been always some people around me. They are my committee members, my family, and my friends! In fact, I am glad that my committee has always kept me up and has made this dissertation better and better. I have to confess that I have never been able to come to this point without their continuous supports. Their patience, encouragements, and challenges have been the actual metaphors to maintain the right track. They have been more than a formal committee! I have been very fortunate to have such a committee with their constructive criticisms, but gentle encouragements.

I would like to sincerely thank for Dr. Moriarty. She has firmly supervised and constructively chaired my dissertation. She has been an excellent motivator, and always maintained her confidence on me. I would not be able to establish such a solid conceptual framework without her invaluable thoughts.

I would like to specifically thank for Dr. Suen. His expertise on statistics, GIS, and methodology has made me better improve the analytical components of this dissertation. He has always provided constructive approaches and suggestions to the issues encountered in this dissertation.

I would like to thank for Dr. Zonta. Her expertise on research design, Census data, and community level indicators has always been projector to reveal the pitfalls in this dissertation. Her suggestions have really augmented the quality of this dissertation.

I really thank for Dr. Lacks. Her expertise on violent crime and policy programs in the City of Richmond has helped me to specify and comprehend essential policy programs related to this dissertation research. Her tremendous efforts on gathering crime data from Police Department have fueled my dissertation research.

And, my wife: Muzehher! She has sacrificed her time and efforts to let me complete this dissertation. Her steady stance has always encouraged me to focus on my dissertation. I really appreciate her supports in this dissertation journey.

And, I would like to thank my family members, colleagues, and friends for their good wishes.

This dissertation is dedicated to my three kids who passed away during this journey: **NILUFER, MUNEVVER, AND REYHAN…**

Table of Contents

List of Tables

List of Figures

Abstract

EXAMINING SPATIOTEMPORAL CHANGE IN NEIGHBORHOOD CRIME USING SOCIAL DISORGANIZATION AS A THEORETICAL FRAMEWORK: A 10-YEAR ANALYSIS OF HOMICIDE IN THE CITY OF RICHMOND, VA

A Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

By Suleyman Demirci, Ph.D.

Virginia Commonwealth University, 2007

Major Director: Laura J. Moriarty, Ph. D.
Professor and Vice Provost For
Academic and Faculty Affairs

This study investigates both space and time aspects of neighborhood crime distributions using social disorganization as a theoretical framework in the City of Richmond, VA. *Neighborhood crime*, in this study, might be considered as any type of index crime aggregated to neighborhood level. For the purpose of the present study, however, neighborhood crime only includes "homicide" categorized as an index crime in the Uniform Crime Report (UCR). Homicides in neighborhoods have been realized as rare events, and have become problematic to establish robust statistical models in the literature. With the focus of neighborhood homicide, this study questions the consistency of Social Disorganization Theory (SDT) by the longitudinal research setting. It, therefore, constructs and verifies seven hypotheses (residential mobility, race/ethnic heterogeneity, family disruption, socio-economic status, population density, youth, and vacancy) to test SDT, while it establishes and further confirms its main hypothesis "Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time."

This study constructs a longitudinal research design with 10 years, uses Census 1990, Census 2000 and homicide data (From the City of Richmond Police Department) as secondary data. Nonetheless, this study uses only two main census decennial years to calculate the other years' structural covariates by the linear interpolation technique such that this study is able to include additional years to construct the essential difference models. Population includes all neighborhoods in the City of Richmond such that this study works with entire population, but no sampling procedure.

As an analytical strategy, this study constructs eleven different binomial logistic regressions, whereas it constructs multinomial logistic regressions as difference models to verify the main hypothesis for neighborhood homicide. Once this study realizes clustered neighborhoods with respect to experiencing homicide hotspot(s), it constructs a stepwise multiple regressions model to explore the most important social disorganization variables for the most problematic neighborhoods.

In terms of findings, the most important social disorganization variables attributed to homicide distribution in the City of Richmond are: The low SES (Socioeconomic Status), residential mobility, vacancy, population density (across only the concentrated neighborhoods), and family disruption.

Accordingly, this study has successfully contributed to the literature around SDT, social crime prevention, and spatially integrated crime policy analysis.

Chapter 1

Introduction

Overview

Understanding the context of crime within urban areas has been crucial for policy makers and researchers (Paulsen and Robinson, 2004). Realizing where and why some crimes occur in certain places and not in others might allow them to suggest more effective policies are needed for preventing and/or controlling crime (Ratcliffe, 2005; Harries, 1999). Getis et al., (2000) also argue location and the reasons of these locations for specific crimes that do not occur randomly in time and space. Therefore, both spatial and temporal analyses of crime distribution have played an important role in directing crime policy programs. In fact, many researchers and crime analysts have studied spatial distribution of crime so as to identify the problematic areas in the city environment. For these purposes, crime analysis aims to uncover the patterns and trends of various crimes across space and time (Boba, 2005).

Researchers and criminologists, on the other hand, have conceptually examined the crime problem in terms of individual and/or structural characteristics (Eck, 2005; Tolan, 2004). On the one side, the researchers mainly focus on the behaviors of both victims and criminals, and therefore, try to explore the relationships between individual characteristics and crimes in the urban areas. On the other side, structural characteristics of neighborhoods have been examined to understand the context of crime. With the assurance, spatial composition of crime occurrences has mostly become related to structural characteristics of localities (Osgood and Chambers, 2000: Sampson and Groves, 1989).

Spatially speaking, the context of crime has been studied by various theoretical perspectives and methodological approaches at certain geographic units (Eck, 2005). Crime analysts and policy makers, therefore, have explained various reasons to understand spatial aspects of crime distribution such as socio-economic development, crime prevention strategies, criminal career adaptations, and contextual characteristics of neighborhoods within the city (Ratcliffe, 2005:103). In this line of reasoning, revealing the neighborhood characteristics and configurations might provide the policy makers and other responsible officials with better intelligence to understand their territories they serve to keep the communities safer.

Accordingly, this chapter initially recognizes the limitations of the present study. Then, it provides very brief background information and theoretical framework as it aims to make the concepts clearer in the mind, and to focus on the main idea of the study. Later, it evidently identifies the purpose of the study, raises its research questions, and describes testable hypotheses. This chapter ultimately recognizes the policy relevance of the research, and addresses the significance of the study.

Limitations

With its longitudinal research setting, this study recognizes certain limitations at the beginning of the research. These are;

- Longitudinal studies at neighborhood level are limited to Census decennial year's data set. Such studies, including the present one, are limited to census geography to operationalize their neighborhood definitions across the city. Worse, census geography in 1990 may not coincide with the census 2000. Studies with longitudinal settings, therefore, need to resolve this issue with certain proxies and spatial methodologies. Otherwise, they cannot compare the neighborhoods over time. Each proxy, rather than actuality, should be considered a limitation in the longitudinal research at neighborhood geography.

- Most neighborhood level studies are constraint with secondary data to measure the neighborhood crime in relation to the degree of neighborhood social disorganization, so does the present study. Accessibility and availability of the crime data in the Police department might often become limited for long term studies. That is, this study could only access homicide incident data in the City of Richmond for the period of time between 1990 and 1999.

- This study particularly limits itself to the degree of social disorganization instead of all other neighborhood characteristics in the City of Richmond. It, therefore, does not account for situational factors. Instead, it only focuses on structural covariates and their changes over time to explore neighborhood social disorganization.

- Due to changes with crime recording systems (UCR & NIBRS) in U.S., this study needs to limit itself to certain period of time. That is, it would be able to work with consistent and comparable crime data over the years.

Accordingly, this study deals with all these obstacles as it thoroughly approaches its research problems.

Background and Summary of Theoretical Framework

In literature, researchers and crime policy makers would like to explore scientific reasons for possible changes in crime patterns at neighborhood level, defined as subsections of the larger community in the city (Sampson and Grove, 1989). In other words, neighborhoods might be considered as ecological units of the communities. The change in contextual characteristics over time might also be utilized to explain possible crime pattern changes in neighborhoods. Neighborhood composition itself does explain the crime variation at cross-sectional form according to the SDT. In fact, the structure of neighborhoods is likely to change over time thanks to citywide social policy programs, financial investments to enhance socio-economic characteristics of communities, and residential movements in the city (Sampson & Morenoff, 2004). Social Disorganization Theory also initiates the chain reaction of disorganization by just starting residential mobility. That is, crime variation can also be explained by increases or decreases of the number of people who might have better and/or worse socio-economic characteristics in the long run. Accordingly, changing neighborhoods might face more /less crime rates or no change over time due to the characteristic differences in neighborhoods.

Crime and disorder might rise depending on the degree of social control at the individual, family, and neighborhood level (Rose and Clear 1996: 1). From the perspective of social disorganization theory, on the other hand, characteristics of safest neighborhoods provide very strong social controls at various levels of the community. Structural approaches, therefore, consider a neighborhood as one unique personality having common values and attributes. Previous studies have primarily utilized social disorganization theory (SDT) to understand the associations between neighborhood characteristics and crime distribution across space. SDT fundamentally addresses that the breakdowns of informal social control might lead to socially disorganized neighborhoods and the more social disorganization the higher rate of crimes in neighborhoods (Shaw and McKay, 1942; Sampson and Groves, 1989). Concentrated disadvantage characteristics, such as residential mobility, minority, family disruption, poverty, unemployment, and more have been revised by the previous studies to address their confounding effects on informal social control in neighborhoods (Paulsen and Robinson, 2004; Sampson and Groves, 1989). From the point of SDT, such social disorganization might, therefore, primarily prepare appropriate environment for higher crime rates. In other words, such disorganized environments might invite criminal activities at such specific neighborhoods, and prepare suitable atmosphere for criminals.

However, some studies address on reciprocal relationships between crime and neighborhood (Sampson et al. 2002: 472). In fact, neighborhoods might impact on the crime distribution as various crimes might shape the characteristics of neighborhoods (Kubrin and Weitzer, 2003: 374). It is really hard to distinguish such two-way interactions at the neighborhood level due to the lack of essentially continuous data over time. Nonetheless, social disorganization theory has been the primary theory to explore the relationships between neighborhood composition and crime distributions within urban areas (Paulsen and Robinson, 2004: 53-73). In the vein of most studies about social disorganization, it is confident that degree of social control is more likely to shape the neighborhood crime rates (Kubrin and Weitzer, 2003).

As a theoretical framework, social disorganization theory (SDT) has guided many studies dealing with contextual (neighborhood) characteristics and crime distribution. However, conceptual definitions of SDT have been operationalized by different variables in the literature (Moriarty, 1999: 15; Paulsen and Robinson, 2004: 62-63). Such variation is more likely to come from the unique characteristics of the locations for different studies (such as state, city, county, and neighborhood). Therefore, each study might have included, somewhat, different contextual characteristics, and operationalized them in the light of SDT. Researchers commonly measure these exogenous variables of social disorganization for different research purposes as they explore spatial aspects of crime, such as residential mobility/stability, family disruption/supervision, racial/ethnic heterogeneity, socioeconomic status, and urbanization. Accordingly, such five exogenous variables of social disorganization theory have been the primary explanatory predictors to explore the variation in crime so far.

Rather than macro level approaches (like neighborhood and city level), on the other hand; some studies primarily deal with micro level (like street segments, street corners, etc) changes to measure crime patterns and trends over time. Researchers like

Taylor (1999) and Weisburd et al. (2004) have, for instance, recently concerned about the change in crime patterns and trends over time. More specifically, Weisburd et al. (2004) addresses the change in crime patterns and trends at street segments by also accounting some limited neighborhood characteristics in their longitudinal research. What they have accomplished is to identify the random and/or consistent crime patterns and trends on the street segments over time. Then, they attempt to attribute these segments with respect to some neighborhood characteristics. Their findings, however, might help law enforcement to reactively approach the crime for such very specifically little places (e.g., street segments) in the city. Weisburd and his colleagues (2004: 51), on the other hand, argue that the choice of street segments might have confounded more common (clustering) crime trends within/between neighborhoods. They missed to explore the changes in spatial crime patterns and trends at neighborhood level. In fact, neighborhood characteristics might be the function of crime patterns and trends at street segments.

Although socio-economic change is considered one possible aspect to explain the reasons of crime variation at neighborhood level, most studies are less likely to examine how socio-economic developments constantly impact on crime patterns and trends over time because there is no available neighborhood level data for shorter periods. In fact, Census 1990 and Census 2000 are actually known as the only sources to examine the socio-economic development in this study, but they may not be enough to measure how crime clusters continuously move, and realize the crime trends due to the socio-economic developments over time. They only provide limited information by such 10 years of time interval (Harries, 1999: 77-78). Such limitation becomes an obstacle to develop longitudinal studies with longer terms so as to explore spatiotemporal aspects of neighborhood crime in terms of socio-economic development. For these reasons, some studies worked with very historic crime data for each 10th year, but most of them could only study at city/county/state levels for examining crime trends over time. Critically, their findings might only give very broad sense about the crime trends without being able to admit various neighborhood characteristics that might confound both crime patterns and trends over time.

Nonetheless, neighborhoods in a city may not change their common characteristics in a very short time, but it takes some time to observe any major changes in neighborhoods. That is why Census Bureau has been gathering the socio-economic level data for each 10 years of time intervals till now. Consequently, the present study would like to realize change in neighborhood configuration as it accounts the change between Census 1990 and Census 2000, and it attempts to explore the changes in crime patterns resulting from such alteration in neighborhood composition.

The intersection of crime variation, neighborhoods with different/similar configurations, and change in the neighborhood composition over time might reasonably derive many conceptual and methodological issues in aiming to thoroughly approach the crime issues across the city. In fact, public policy creates ambiguities as it deals with multi-dimensional social phenomena (Ripley, et al., 1991). When considering the change in contextual characteristics of societies over certain period, crime distribution might also vary within neighborhoods. Then, the following questions remain to answer: Are there any neighborhoods that experience any change in crime rates over time? Further, one might wonder if there are similar neighborhoods that confirm consistent increases/decreases in crime variation over time. More importantly, is there anyway to differentiate specific neighborhoods that remain stable as opposed to others experiencing random crime variation over time?

Methodologically, one should establish some trajectories (groupings) for the neighborhoods so as to examine patterns in relation to various neighborhood compositions over time. In fact, the present study needs to come up with reliable neighborhood classifications with respect to social disorganization theory. It should also account similar neighborhoods showing clusters by their specific contextual characteristics in the city. The present study, therefore, is supposed to account possible spillover impacts of both contextual changes and crime rate changes from certain neighborhoods to others. In other words, some neighborhoods might become spatially associated across the urban setting. Therefore, they may, or may not, derive similar crime variations over time. Interestingly enough, Shaw and McKay (1942), Sampson and Grove (1989) and many of the following studies retesting social disorganization theory have not taken such possible spatial dependency into consideration. Accordingly, the present study has to investigate, and cope with possible spatial association across the neighborhoods in relation to crime variation.

Taken together, this study attempts to revisit these concepts, and contribute to the knowledge of the discipline by focusing on the spatiotemporal (space and time) changes in crime patterns at the neighborhood level and using these results to impact policy resulting in this research having strong policy relevance.

Statement of Problem

This research is primarily concerned about whether change in *neighborhood crime* is likely to be associated with the change in certain structural characteristics of neighborhood composition as it accounts for the factors of Social Disorganization Theory over time.

> *Neighborhood crime*, in this study, might be considered as any type of index crime aggregated to neighborhood level. For the purpose of the present study; however, neighborhood crime only includes "homicide" categorized as an index crime in the Uniform Crime Report (UCR). Therefore, "Neighborhood Homicide" is phrased in this study as Morenoff and Sampson (1997:31) appropriately utilized it to examine violent crime in relation to spatial dynamics of socioeconomic disadvantage.

In fact, it expects to realize possibly significant association between neighborhood homicide change and neighborhood social disorganization change over time. In literature, many studies have been concerned about testing Social Disorganization Theory, and investigated the association between crime and social disorganization so far. In their findings, more socially disorganized neighborhoods are more likely to be associated with more neighborhood crime.

Although previous studies realized very consistent findings to support Social Disorganization Theory, few of them have focused on change processes to test Social Disorganization Theory. That is, the literature constructed by previous research on such relationship between crime and social disorganization is still incomplete. In fact, it is necessary to explore whether social disorganization change over time remains a strong predictor of neighborhood crime change. Rather than simply pinpointing the association between social disorganization and crime distribution, there is a specific need to construct such a model that explains the association between neighborhood social disorganization change and neighborhood homicide change over time.

This study, therefore, wants to reassure about the consistency of Social Disorganization Theory (SDT) in different population by constructing difference models to account the changes in both neighborhood homicide and neighborhood social disorganization over time. In literature, SDT has frequently been tested in similar cities such as Chicago, Baltimore, British cities, and large metropolitan cities so far. There is also much need to study Social Disorganization Theory in smaller cities such as the City of Richmond. In fact, tremendous variation of homicide incidents over time has been so questionable in the City of Richmond; none has studied homicide with respect to the predictors of Social Disorganization Theory in the City of Richmond. In specific, few studies have dealt with homicide incidents at neighborhood level in the literature, since they are known as very rare events for the neighborhoods. Instead, researchers have just preferred to study homicide at either City level or larger scales to avoid from the constraints of rareness. Therefore, studying homicide in relation to structural context at neighborhood level has been problematic so far. Accordingly, the major concerns in this study are related to test Social Disorganization Theory, and to handle methodological obstacles for constructing difference models.

Purpose of the Study

The present study primarily aims to explore the associations between neighborhood social disorganization and neighborhood homicide in the longitudinal research setting. More importantly, this study attempts to explore neighborhood homicide pattern changes with respect to the changes in neighborhood configuration between two Census decennial years. During this period, the social and economic characteristics of neighborhoods altered from 1990 to 2000. This study further calculates the neighborhood social disorganization scores by performing linear interpolation based on such two main time steps. It, therefore, suggests using such changes in neighborhood composition so as to explain the changes in neighborhood homicide patterns.

For the rareness of the homicides across the neighborhoods, this study aims to construct robust logistics regression models over individual years and subsequent year ranges between 1990 and 2000. It ultimately specifies certain neighborhoods experiencing homicide hotspot(s) in this period, and attempts to construct a multiple regression model in these neighborhoods only. This study, therefore, avoids from the rareness of the homicide, as a neighborhood crime, and develops a solid methodology to cope with the unique characteristics of the homicide distribution in the City of Richmond.

Accordingly, central concern of the present dissertation research is to explore possible neighborhood homicide variation associated with the change in neighborhood composition with respect to social disorganization, and to test neighborhood predictors of social disorganization theory over time.

The present research, therefore, systematically aims to:

- Explore any relationships between neighborhood characteristics and neighborhood homicide.
- Examine any consistent increase/decrease and stable neighborhood homicide in similar neighborhoods over time.

- Investigate any unusual neighborhood homicide variation over time as it accounts the factors of Social Disorganization Theory.
- Explore if change in neighborhood homicide is associated with the change in neighborhood social disorganization over time.

Research Questions and Hypotheses

The present study has the following research questions subsequently related to each other:

- Is neighborhood homicide associated with social disorganization?
- Which elements of social disorganization have the largest impact on neighborhood homicide?
- Does the change in neighborhood social disorganization explain the change in neighborhood homicide over time?

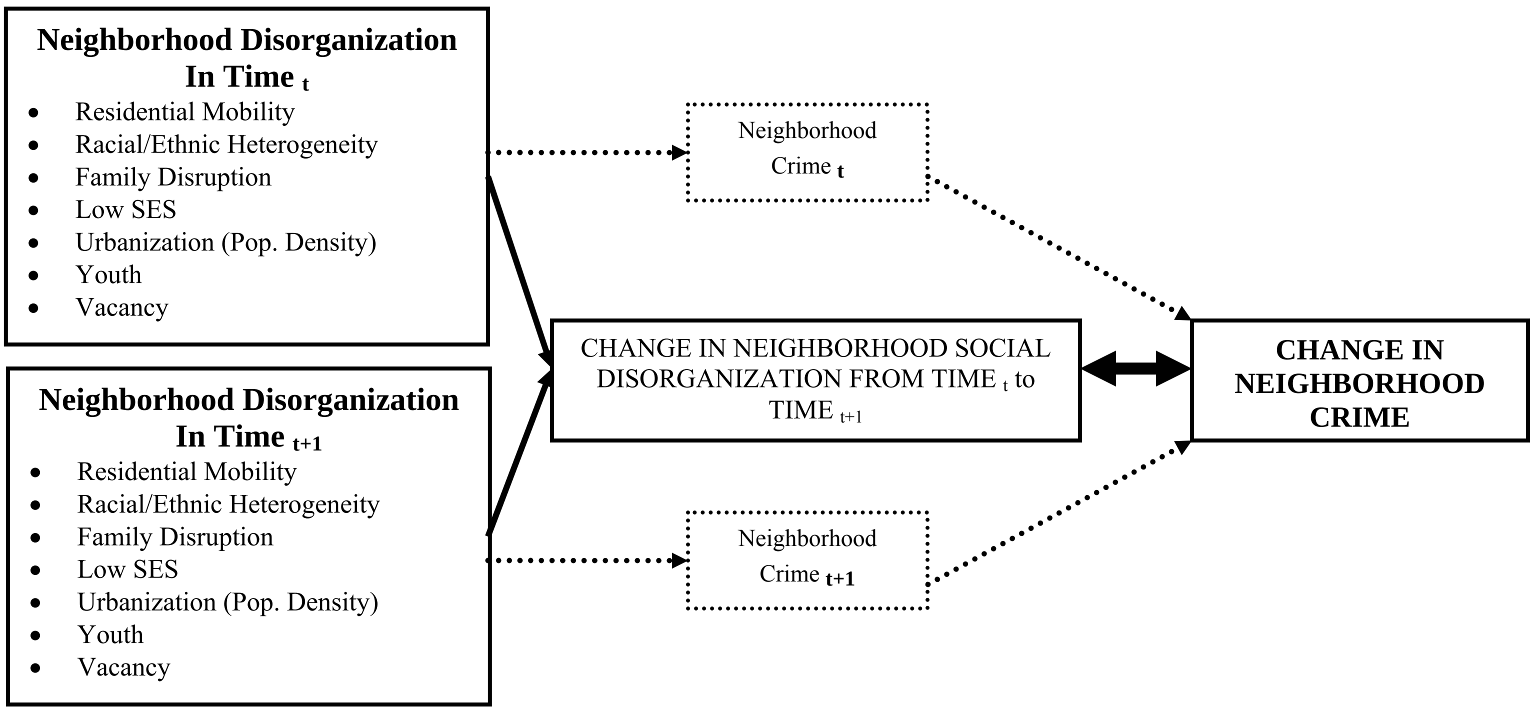
The present research wants to retest Social Disorganization Theory as it answers the first two research questions above. The last research question, on the other hand, aims to explore possible *relationships* between the change in neighborhood social disorganization and neighborhood homicide variation over time. Although conceptual framework (Figure 1.1) addresses any type of index crime aggregated to neighborhoods, homicide becomes the focal point for the purpose of this research. This study, therefore, constructs the following testable hypotheses for only neighborhood homicide:

- H_1: As "residential mobility" increases so does the neighborhood homicide**.**
- H_2: As "race/ethnic heterogeneity" increases so does neighborhood homicide.
- H_3: As "family disruption" increases so does neighborhood homicide.

- H_4: As "socio-economic status" decreases so does neighborhood homicide.
- H_5: As "population density" increases so does neighborhood homicide.
- H_6: As "youth population rate" increases so does neighborhood homicide.
- H_7: As "vacancy rate" increases so does neighborhood homicide.
- H_8: Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time.

Accordingly, the main hypothesis of this research is "Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time." The study ultimately constructs difference models as it tests the principal hypothesis as well as other testable hypotheses of Social Disorganization Theory. These hypotheses are tested for only homicide, UCR (Uniform Crime Report) type incidents in the City of Richmond. Homicide has been the most problematic violent type of crime, and has become one of the most questionable crimes in the City of Richmond (Rosenfold, et al., 2005)

Figure 1.1: Conceptual Model* for Neighborhood Crime Change Associated with Change in Neighborhood Social Disorganization



Unit of Analysis : Neighborhoods
Neighborhood crime : E.g., Homicide aggregated to neighborhoods

* Adapted from Sampson and Groves' Model, 1989

Policy Relevance of Research

"Policy making is always contextual in that it necessarily comes out of a time and place..." (Shafritz, et. Al, 2004: 1). City wide crime policies, therefore, might require thinking contextually on how crime is distributed across neighborhoods. In fact, the present study focuses on the change in spatiotemporal (space and time) aspects of neighborhood homicide. It attempts to explore the associations between neighborhood homicide and certain contextual characteristics of neighborhoods. And, it acknowledges the roles of various policy programs being implemented citywide and/or in certain neighborhoods. Besides the concerns about the changes in crime patterns, crime analysts, criminologists and policy makers are more likely to investigate unusual variations as they normally expect more crime rates in more socially disorganized neighborhoods. This might become more important as one acknowledges the potential functions of various policy programs implemented across the city.

Therefore, various methodologies and procedures have been adopted for policy analysis to capture such variation in the neighborhoods. In fact, public policy analysis might be explained as an analytical tool for problem solving (Shulock, 1999; Weimer and Vining 2002). Such analytical model is supposed to resolve the problem of optimal allocation, deployment, and conception of rationality when addressing policy problems (Majone, 1990). Policy analysis can, therefore, align the existing policy to the whole picture, and to produce a cohesive image.

As Weimer and Vining (2002: 23-38) argue for the necessity of an analytical framework as a problem solving methodology for policy analysis, various analytical methodologies might provide decision makers with "advice" on how to initiate optimal strategies and outcomes to better understand the nature of neighborhood homicide. Accordingly, the crime problem might be identified with its spatiotemporal (both space and time) dimensions and then decision makers might place the issue on the public policy agenda for active consideration. At this point, King and Zeng (2001) posit the first order difference modeling as a more informative policy analysis methodology to study the impact of various policy programs for international affairs. With the difference modeling approach, neighborhood policy analysts may also want to measure the explanatory power of social disorganization predictors on neighborhood homicide change over time. This study, therefore, applies the similar methodology to explore the possible association between change in neighborhood social disorganization and the change in specifically homicide (as a neighborhood crime) over time.

As considering the particular interests of the present study, understanding patterns of neighborhood homicides over time might be invaluable to explain where they mostly and frequently occurs in a city, and what sources and approaches might be necessary to handle problematic areas (Greene, 2000: 22). Further, local government with police organizations might initiate more effective policies to enhance further public awareness against crime in their neighborhoods. The inhabitants realizing the significant role of informal social control in their neighborhoods might be better link between the officials and the community. Such collaborative approach might result in less crime issues over time. The possible findings of this study might, therefore, allow identifying some neighborhoods in which it might be necessary to further improve social cohesiveness.

Because of the limited resources, policy makers actually need to approach crime issue at contextual level (neighborhood level) to avoid possible crime displacement effects at micro scales, and had better develop community level strategies to thoroughly combat with general neighborhood crime issues. Community level approaches might, therefore, develop social cohesiveness and common sense against crime in their territories (Sampson & Morenoff, 2004:251). General hypothesis of Social Disorganization Theory would be that higher informal social control is less likely to derive crime issues in the neighborhoods. Exogenous variables of Social Disorganization Theory, on the other hand, are likely to determine the degree of informal social control in the neighborhood context. Accordingly, contextual approach with the components of Social Disorganization Theory is congruent with policy analysis consideration.

In the turning point of policing in U.S., problem oriented policing depicts a way to broaden the input to enhance the policing so that the police are able to solve problems instead of simply responding to specific incidents (Boba, 2000). For this purpose, problem oriented policing suggests that police managers need to understand the trends and patterns of problematic areas instead of just focusing on one incident (Rosenbaum and Lurigo, 1994). It, therefore, requires information driven policing instead of incident driven policing (Boba, 2006; Harries, 1999). To enhance such policing, the present study attempts to explore neighborhood homicide pattern change associated with the change in neighborhood context over time.

Accordingly, the concept and methodology of the present research have relevant components to study homicide policy analysis and further propose prevention strategies for the City of Richmond.

Significance of the Study

Significance of this study relies upon three interrelated components such as theory, methodology, and policy consideration.

Theoretically, this study tests Social Disorganization Theory (SDT) in different population. It further attempts to expand Sampson and Grove's model (1989) as it includes two more social disorganization indicators into their landmark model. In fact, the City of Richmond, with its unique crime (such as homicide) and social disorganization characteristics, might become a more feasible location to study the consistency of Social Disorganization Theory over time. From the point of selecting such population, this study becomes a unique research opportunity that has never been done in the City of Richmond. Among violent crime, homicide might differently change with respect to change in social disorganization from one year to another. Such variation with respect to year difference might also be reasonable way to realize the consistency of SDT in the same city.

In addition to testing traditional factors of SDT, this study contributes to the literature such that SDT supports to explain the neighborhood homicide variation by the changes in neighborhood social disorganization over time. This study, therefore, enables to realize the consistency of SDT as it explores the changes in both neighborhood homicide and social disorganization. Therefore, the intersection of exploring the contextual reasons for homicide pattern changes, and realizing various neighborhood configurations changing over time allows the officials to develop comprehensive and integrated approaches so as to understand spatiotemporal (Space and Time) aspects of neighborhood homicide.

Methodologically, the present study designs a longitudinal research, and develops various difference models to capture the possible changes in neighborhood homicide trends/patterns with respect to the changes in neighborhood social disorganization over time. Such methodological approach with difference model might, therefore, provide more viable information about the associations between neighborhood configurations and neighborhood crime than a cross-sectional research design does. That is, analytical mechanism in this study can also be applied for any type of neighborhood crime to test SDT in different cities. Applicability of such methodology might, therefore, be an optimal strategy for neighborhood policy analyses.

From the view of policy consideration: The findings of this study might recognize that not only should police organizations be concerned about crime issues, but other governmental units should also be concerned and involved with police organizations. That is, specific findings at neighborhood level might call either a joint-force or task force against homicide at local level if one accounts various dimensions of homicide phenomenon, including attributes of neighborhoods, enforcement efforts, and various policy implications. Once the present research realizes such homicide pattern changes across neighborhoods with respect to possible changes in neighborhood configuration, policy makers and/or other responsible officials in the city would make more consistent decisions on neighborhood strategies. More specifically, findings of the present study might allow the police to enhance their neighborhood intelligence (knowledge) for better communication between officials and the community, for having safer environment, and also for better understanding the neighborhoods that the officials serve to. More deeply, the police would better recognize various reactions of the neighborhoods as how neighborhood homicide is differently associated with the changes in their neighborhood composition over time. Accordingly, the present study expects to recognize specific neighborhoods that are more vulnerable to specific degree of neighborhood homicide over time.

From the points of theoretical, methodological, and policy consideration, exploring the function of neighborhoods' changes on neighborhood homicide variation might provide better understanding with the components of Social Disorganization Theory. By acknowledging the crime policy programs (e.g., Project Exile), the findings are also be interpreted by outcomes of these programs implemented through the study period of this research. Accordingly, the present study becomes presumably interesting addition to the literature around Social Disorganization Theory, social crime prevention, and spatially integrated crime policy analysis.

Chapter 2

Literature Review: Theoretical and Empirical Contributions

Overview

The literature review in this study consists of various interrelated themes including, terminology settings for the study, policy oriented crime prevention strategies, Social Disorganization Theory from past to present, recent studies on Social Disorganization Theory, and the select researches for structural context in relation to neighborhood crime. In fact, it specifically focuses on the literature to review the studies for homicide in relation to structural context. Ultimately, it will link these components together and to the purpose of this study.

Terminology Settings

Crime Analysis

Crime analysis may be defined as "a set of systematic, analytical processes directed at providing timely and pertinent information relative to crime patterns and trend correlations to assist operational and administrative personnel in planning the deployment of resources for the prevention and suppression of criminal activities, aiding the investigative process, and increasing apprehensions and clearance of cases," (Gottlieb, Arenberg, & Singh, 1994, p.13). Thus, the goals of crime analysis are: processing information in a timely manner, and preventing and controlling crime based on accurately processed information. According to Reuland (1997), crime analysis identifies "trends and patterns within crime data in an attempt to solve crimes or prevent their repeat occurrence" (p.53). In a contemporary crime analysis unit, there are three distinct areas of analysis: strategic crime analysis, tactical crime analysis, and administrative crime analysis (Haley, Todd, and Stallo, 1998). These methods are presented below.

Tactical Crime Analysis

Tactical crime analysis can be classified into three categories. Crime pattern/series deals with separate events and analyzes crime patterns in terms of day/time, location, clusters, and previous similar crimes. Using these analyses makes it easier to predict areas of need and to direct human resources. In tactical crime analysis, Crime-suspect correlation is an essential procedure that provides correlational data between possible suspects and particular crimes. The correlation may be obtained by analyzing criminal histories and other intelligence data supplied by other agencies and sources. Finally, crime analysis develops target suspect criminal profiles in order to better examine and scrutinize specific types of offenders, such as sex offenders. This kind of data may also be used to take proactive steps to control crime in a community (Haley, Todd, and Stallo, 1998). From the perspective of crime analysis, tactical approach supports current law enforcement operations to make them more successful (Schneider, 1994).

Strategic Crime Analysis

In strategic crime analysis, analysts are concerned with the future trends of crimes and the quantitative measurement of a wide range of crimes (Godfrey and Harris, 1971).

Crime trend forecasts, resource allocation, and situational analysis are also involved in this category (Haley, Todd, and Stallo, 1998). Future crime tendency projections are based upon past and current information so that managers can make smarter decisions in the planning phase (Schneider, 1994). Resource allocation analysis uses a cost-benefit analysis to verify the best possible use of personnel for maximum efficiency (Stallo, 1997). Situational analysis further offers dynamic beat configuration and planning by accounting demographic data including victims' experiences (Boba, 2005; Rossmo, 2000).

Administrative Crime Analysis

Administrative crime analysis studies policy development and the rationalization of the use of resources (Gottlieb, Arenberg, Singh, 1994). This type of analysis results in the creation of reports such as annual crime reports. Such administrative approach in crime analysis should be considered the process of bringing results of both tactical and strategic crime analyses together (Boba, 2005: 245). The administrative crime analysts, therefore, prepare appropriate presentations to police chief, city administration, and other stakeholders. Periodic bulletins and reports are conveniently distributed by administrative crime analysts. In a way, administrative crime analysis unit informs the public about crime and their policy activities. Accordingly, they extensively utilize digital technologies (i.e. Internet web pages) to disseminate the essential crime information to all stakeholders.

Reuland (1997) identifies four essential tasks of modern crime analysis unit as: analyzing crime and criminals to determine the allocation of resources, assisting investigators in identifying crime-suspect relationships, accurately reporting crime trends and patterns, and assisting with the prevention of crime. One of the most significant functions of crime analysis is to proactively prevent crime or to support crime control and prevention. Moreover, crime analysis helps to reduce the response time for the police operations.

Crime analysis units are, therefore, established to serve for the purpose of law enforcement, and to investigate various types of crimes. Large agencies often divide their crime analysis units into specialized units focusing on narcotics, forgery/fraud, homicide, and intelligence. Clearly, the function of crime analysis changes depending on the department in which it is conducted. In short, law enforcement organizations benefit from the advantages of crime analysis techniques to enhance tactical, strategic, and administrative policing as they effectively and efficiently deploy law enforcement resources. Crime analysis has been improved and made more effective with technological innovations, such as GIS. GIS is discussed next, as it is one of the most important innovative frameworks for crime analysis today.

This study primarily focuses on strategic crime analysis with its neighborhood based approach to explore the change in neighborhood homicide in relation to the change in social disorganization over time.

Geographic Information Systems

This study utilizes multiple analytical techniques to prepare and analyze the essential neighborhood homicide and neighborhood structural data to answer its research question(s). Among them, this section aims to review the Geographic Information

Systems and its important role in the consideration of both public policy and administration.

Geographic Information Systems are powerful technological tools for law enforcement agencies and other public sector. They are useful for various levels of employees in the organizations. For example, typical GIS users in law enforcement organizations include crime analysts, computerized crime record management personnel, police executives, patrol leaders, and more (Boba, 2000). GIS is a computer based system that captures, stores, manipulates, analyzes, displays, and queries geographic data (Greene, 2000). Such geographic data in law enforcement, for instance, would be relevant to include points (crime incident location), lines (streets), and areas (precinct boundaries like cities, counties, districts, and neighborhoods) (Boba, 2005; Rossmo, 2000). From the point of view of the police, these geographic features and the crime incidents with location information can easily be layered and viewed in GIS environment. Ability to visually layering features with its spatial analysis capabilities distinguishes GIS from other information systems, which can only promote textual tables, and makes GIS more useful to analyze vast amount of spatially related data (Boba, 2000). That is; such layering capability provides police managers, policy makers, and crime analyst with an excellent analytical framework to notice the changes in the clusters of crime incidents, to deploy appropriate personnel, and allocate essential resources to the specific locations in which crime clusters become problematically change (Harries, 1999). Noticing the changes in such clusters and policing with such information might, therefore, improve human resource management, other deployments and allocations in law enforcement organizations. Law enforcement organizations with essential components of GIS framework might ultimately become learning and high performing organizations.

Geographic Information System (GIS) realizes the significant role of location based information in public policy analysis (Greene, 2000). This information is mostly referred as spatial information. In fact, the policies for urbanization and public management are more likely to be related to location based information (Lopez, 1996). Therefore, urban planners and policy makers need to deal with the characteristics of locations in order to interpret the urban and community problems and establish the most suitable solutions (Masser, 1998). To deal with these issues, GIS, again, becomes one of the best frameworks to establish an effective and efficient knowledge platform to drive modern policing today (Hirschfield, 2001). Further, such location based information in the database enables to forecast the possible future crime patterns and trends in various jurisdictions (Pease, 2001). Considering the contributions of GIS above, GIS can be realized as a socially constructed technology as compared to other information technologies (Innes and Simpson, 1993).

Because GIS can be utilized for integrating and merging such data coming from different organizations, it can promote smoother information sharing processes among the organizations (Innes and Simpson 1993). Of the contributions, GIS potentially fosters law enforcement to serve a new community leadership role as existing crime databases are integrated with GIS databases for planning in other public agencies, such as taxation, education, transportation (Garson and Vann, 2001).

Accordingly, GIS (Geographic Information Systems) has been increasingly recognized within the law enforcement community as an efficient and effective tool for the analysis of crime patterns, the allocation of the enforcement resources, and the support of strategic planning in the organization (Harries, 1999). Therefore, law enforcement agencies across the country are making major investments for GIS infrastructure. Constructing and utilizing such innovative technology is more likely to provide the agencies with more intelligent and analytical way of policing (Canter 2000).

Taken together, GIS can be utilized for the following purposes;

- To display, analyze, and distribute spatial and non-spatial data
- To integrate various data sets
- To provide an analytical framework for problem solving
- To promote effective decision making and intelligent resource allocation and deployment
- To explore spatial dependency and pattern across the predefined contiguous state/city/neighborhood boundaries
- To promote location based police intelligence

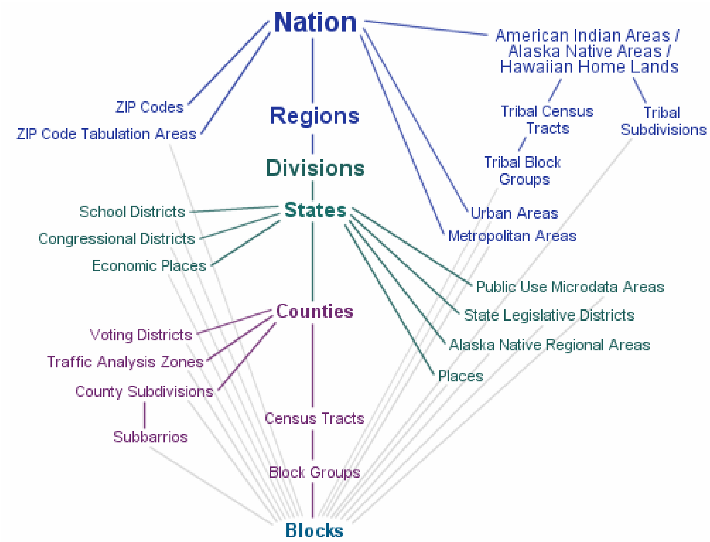
More specifically, this study posits that GIS methodology with its essential components can enhance the policy analysis for neighborhood effects on crime variation. That is, it pinpoints spatial pattern of neighborhood homicides by GIS and other geo-statistical software packages. Such an approach in this study should not be considered only thematic mapping of the incidents. Rather, it statistically constructs one hypothesis and attempts to test it through advanced geo-statistical tools. Then, it ultimately determines the level of spatial pattern and dependency for the neighborhood homicides across the City of Richmond.

Neighborhood Definitions and Census Geography

In neighborhood level studies, social ecologists and geographers recognize that the concept of neighborhood has not addressed a unique approach (Sastry et al., 2002: 2). Even local residence might define their neighborhoods as either their certain territory in which they work or shop. From the perspective of residents, therefore, neighborhoods' boundaries might become relatively unstructured depending on how they see their territories. In fact, neighborhoods should be considered as the subsection of the large communities within the city boundary. They might indicate either isolated communities and/or with various characteristics. However, they might show certainly unique structural characteristics in some degree. With these issues on defining neighborhoods, Sastry and her colleagues (2002), therefore, have investigated residences' neighborhood definitions as they study how neighborhoods matter about regular activities of children in Los Angeles, CA.

Although residences' subjective perception varies to describe their physical boundaries of neighborhoods, official boundaries might be structurally different than their perceptions. Further, social ecologists or other social policy researchers might differently define neighborhoods. To be consistent on the researches, they have frequently employed Census geography to operationalize the neighborhoods in their studies. That is, various units of census geography, such as census tracts and block groups, have been promising the proxies of neighborhoods in literature.

Figure 2.1: Census Geography



Source from Census Bureau: http://factfinder.census.gov/home/en/epss/census_geography.html

As seen in the Figure 2.1, the census geography varies from Census Blocks to the entire United States. From bottom to the top, this figure also shows certain hierarchical structures amongst the census geography. Instead of dealing with all details of census geography, this study specifically exemplifies the possible neighborhood proxies in terms of census geography and their hierarchy to their upper/lower level census geography. For instance, the smallest census geography to define neighborhoods might be census block groups. They are just upper level of census blocks. Then, they are geographically coincided to the census tracts. That is, one census block is the subsection of one block group, whereas one block group is just one subsection of a tract. All their boundaries in the same Census year exactly coincide to each other. Census Blocks, Block Groups, or Census tracts become the subsection of a county and/or city according to the hierarchy of census geography. However, Census boundaries at Census Block Groups may not be compatible to each other due to the changes in the boundaries from one Census year to another. This deficiency has become an issue in this study. To fix the deficiency and set an appropriate longitudinal framework, I have just purchased the Census 1990 data and its boundary normalized to Census 2000 (See Appendix A). The methodology used to normalize Census 1990 geography to Census 2000 is provided by this vendor and attached in the appendix.

Depending on the size and structure of the city, researchers might prefer to use either census block groups or tracts as proxies in their neighborhood level studies. In fact, this study employs census block groups as the most convenient proxy to operationalize the neighborhoods in the City of Richmond. That is, the City's official neighborhood boundaries are better coincided with census block groups. Since the neighborhood level proxy variables are distributed with respect to the census geography, this study definitely utilizes census block groups as the best proxy to work with neighborhoods in relation to crime distribution in the City of Richmond, VA.

How Police Record Crime in U.S?

Police departments do not record the crimes regardless of any rationality behind. In fact, FBI gathers, and records all state/city/county level crimes in their databases (Lynch & Addington, 2007). They have to keep crime data with some certain attributes and structures. Police departments in U.S., therefore, are supposed to follow certain definitions and instructions as they maintain and update their local crime records. Having certain rules and instructions are more likely to result in working with valid and reliable crime data. And, crimes are, therefore, recorded by the same definitions and procedures across the country. There are two primary crime report systems in U.S., such as UCR (Uniform Crime Report) and NIBRS (National Incident Based Reporting System) (Lynch & Addington, 2007).

UCR versus NIBRS:

The logic of UCR is quietly different than NIBRS. UCR should be mostly considered as a summary crime data, whereas NIBRS covers all crimes that occurred in an incident (Roberts, 2005). Accordingly, the number of incidents in NIBRS is supposed to be slightly higher than UCR does. NIBRS should be considered as the expanded version of UCR system.

Another huge difference between UCR and NIBRC is that Group-B offenses in NIBRS are called as arrest offenses (Lynch & Addington, 2007). All others including index crimes of previous UCR are classified in NIBRS Group-A. That is, some Part-II arrest offenses are classified in NIBRS Group-A, whereas some are classified in Group-B. According to NIBRS, all offenses have to be separately recorded, whereas only Group-B should be classified if some certain offenses result in arrest. Therefore, these parameters might make the UCR/NIBRS conversion complicated, and further wrongly specified.

The Uniform Crime Reports, gathered by FBI (Federal Bureau of Investigation) since 1975, give a nationwide view of crime based on statistics contributed by state and local law enforcement agencies (Lynch & Addington, 2007). Each police department is supposed to record the crime data in specific format defined by FBI. The crime data were recorded by UCR format in the City of Richmond till 1999. Then, FBI changed the UCR format into NIBRS system in 2000. Unfortunately, new format is quietly different than UCR, and is not directly compatible to each other.

UCR data includes aggregate counts of offenses and arrests in the states/cities/counties (Roberts, 2005:1). However, the existing offenses were not supposed to result in an arrest in UCR system. They are all reported offenses. In fact, UCR summary system was classified by two groups, such as Part-I and Part-II. Notably, Part-I of UCR can only accept the most serious offense in each incident. Each incident, however, might include more than one type of crime. That is, these crimes are considered the most frequently reported offenses and the best indicators of neighborhood crimes. More importantly, UCR decides the most serious crime by *hierarchy rule* (Lynch & Addington, 2007). These crimes in Part-I include, with the right order, criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, and arson. Nonetheless, arson is not classified in the hierarchy. It can be recorded if only arson crime is committed in an incident. Further, all these crimes are called as index crime, and they are supposed to be recorded with some detailed information such as offender/victim information, and type of weapon(s) used for such index crimes.

Part-II offenses, on the other hand, are defined as all other crimes left out of Part-I offenses (Roberts, 2005). However, they can only be recorded if they result in an arrest. Further, they don’t have any hierarchy among them. The criterion is whether such type of crime results in an arrest or not. Accordingly, Part-II offenses are classified as arrest offenses in UCR system. These include other assaults, forgery/counterfeiting, false pretenses/swindle/confidence game, embezzlement, stolen property offenses, destruction/damage/vandalism of property, weapon law violations, prostitution & commercialized vice, sex offenses (except rape and prostitution), narcotic drug laws (2 offenses), gambling, offenses against the family, driving under the influence, liquor law violations, public drunkenness, disorderly conduct, all other offenses (except traffic), curfew/loitering, runaway, and juvenile.

Accordingly, if one incident includes more than one type of offenses, then UCR captures only the most serious one according to the hierarchy rule. Nonetheless, Part-I offenses must be classified among themselves, whereas no classification among the Part-II. Meaning that, UCR might miss many part-II offenses if such offenses do not result in any arrest and/or part-II crimes occur together with one of the part-I crime.

Note that this study constructs a longitudinal research design so as to answer its research questions. In fact, longitudinal studies require many time intervals to examine the crime patterns and trends over time. If one wants to study a working period that includes both UCR (Uniform Crime Report) term and NIBRS (National Incident Based Reporting System) term, researchers might have faced some data manipulation and compatibility issues.

As a result of the characteristics of UCR format, the present study had better work with index crimes (Part-I) as the most convenient neighborhood crime proxies. All index crimes aggregated to the neighborhoods might be the concern of this research if the crime data are available between 1990 and 1999. However, instead of all, it only focuses on one of the index crimes (e.g., homicide) for the purpose of the research due to the limited accessibility for the crime data in the City of Richmond Police Department. Since UCR type crimes and NIBRS type crimes are not compatible to each other, this study has to work with only UCR type crimes, such as homicide, as it tests Social Disorganization Theory in the City of Richmond, Virginia. For instance, it requires certain period of time for the research to conveniently study both the change in neighborhood homicide and the change in neighborhood social disorganization in a longitudinal setting.

Homicide as a Neighborhood Crime

This study only focuses on certain neighborhood homicide classified as index crimes for the following reasons: First, to obtain consistent and valid data for the analysis since the police department is supposed to prepare comprehensive index crime data for FBI's UCR (Uniform Crime Report) database; Second, to narrow down the scope of the study instead of dealing with all types of crimes that might be classified differently from one police department to another; and third, to generalize the findings of the study since all other law enforcement units are supposed to report the same index crimes to FBI. According to the UCR codebooks, index crimes include murder, rape, assault, robbery, burglary, arson, larceny, and motor-vehicle theft. Index crimes can also be classified as violent and property crime. Violent crimes include murder (homicide), rape, assault, robbery, and arson, whereas property crimes include burglary, larceny, and motor vehicle theft according the formal UCR codebooks. As the most problematic crime in the City of Richmond, this study just deals with homicide, defined as directly quoted from the codebooks (ICPSR, 2002:104-120):

Homicide Offenses (murder in UCR): "The killing of one human being by another."

Accordingly, this study selects homicide as one of the violent type of crime in the UCR for the purpose of research.

Policy Oriented Crime Prevention Strategies

Numerous methods have been implemented to respond to the crime problem. Tolan (2004) contends that strategies for crime prevention might be very diverse on understanding the root causes of crime, and might include various approaches in reducing crime rates. Policing, economic policies, neighborhood watch programs, and incarceration programs are all considered to be crime prevention efforts. To Tolan (2004: 109), crime prevention programs aim to "prevent the onset of criminal activity in individuals or the occurrence of criminal activities within a given location." According to this definition, crime prevention might essentially deal with crime trends and patterns, and/or locations of crime clusters. Prevention, therefore, basically aims to avoid the crime hotspots within specific locations and to reduce the overall crime rates within cities. Changing characteristics of neighborhoods, where more crime occurs, might also trigger more crime clusters at the neighborhood level. Examining these hotspots of crime from the point of various neighborhood characteristics might potentially allow preventing more crime as compared to addressing individual behaviors. Therefore, policy research might deliberately inform the efforts to control crime, and might fulfill the knowledge on the causes of crime at the contextual level (Wilson and Petersilia, 2004: 1-3).

Tolan (2004: 111) classifies three unique characteristics of crime prevention programs, such as situational, community-oriented, and developmental strategies.

Situational Crime Prevention Programs

Situational approaches mostly refer to the efforts to treat the individuals, and immediately influence the criminal activities in short run. As one of the well known researchers, Clarke (1995) contends that criminals primarily develop rational choice to evaluate the risks and opportunities of committing crime in certain places. Therefore, crime might be clustered geographically based upon more opportunistic places. The policies, then, are implemented to eliminate these clusters at very specific places such as the corner of the street and stores. Among the solutions, "target hardening" approach is most commonly implemented to reduce the crime rates at specific places (Talon, 2004:112). However, situational strategies may not be considered effective at the neighborhood level, since they are mostly implemented to a very specific problem at a very specific place.

Consequently, crime is often displaced to somewhere else due to the situational crime prevention approaches. Therefore, the total crime rate within both neighborhood and/or city may not lessen by situational crime prevention strategies.

Community-Oriented Crime Prevention Programs

Community-oriented approaches, on the other hand, assume that most of the crime distribution might be explained by macro-social factors (Sampson and Groves, 1989). Socio-economic conditions, race/ethnic composition, and other community characteristics might be considered as macro-social conditions for neighborhoods (Paulsen and Robinson, 2004: Cahill, 2004). Further, these macro-social conditions can also influence the micro-social relations within communities (Talon, 2004:113; Weisburd et al., 2004). That is, as leaders of community-oriented crime prevention strategies, Shaw and McKay (1942) emphasize that neighborhood characteristics can explore the variation within crime more than individual approaches can.

In fact, individuals do not live in a vacuum, but they are under the influence of neighborhood composition (Sampson and Groves, 1989). To this view, risk factors for crime are mostly explained in ecology of risks for crime, and the informal social controls determine the quality and viability of neighborhoods (Talon, 2004:114). As policy solutions in this approach, policy makers try to enhance informal social controls by making institutional investments in the neighborhood, and therefore, they would like to mitigate the ecological risks against crime occurrences. The critical questions, then, are to determine whether such neighborhoods provide the appropriate environment for crime clusters, and to decide how these neighborhoods should be developed by which specific neighborhood strategies, investments, and interventions.

Developmental Crime Prevention Programs

Developmental crime prevention strategies fundamentally aim to eliminate the risk factors within individuals and/or the family apart from context (Talon, 2004:117). Developmental prevention strategists are supposed to determine which individuals tend to be delinquent in terms of aggressiveness, lack of self-control, and early rule breaking. However, these crime policy researchers may not easily distinguish developmental effects. Further, early delinquency tendencies may not directly address the current behavioral level of individuals. That is, developmental strategists shift to social ecological views to enhance their approaches (Tolan and Gorman-Smith, 1998).

Accordingly, ecological views might still be considered the most appropriate approach as the present study examines the neighborhood homicide in response to various degree of social disorganization.

Crime Policy Programs in the City of Richmond, VA: 1990-1999

This research has realized two main crime policy programs in the City of Richmond during its study period of time from 1990 to 1999. Rather than making program evaluation, this study aims to review the objectives and outcomes of these programs in literature. Once it clearly acknowledges their outcomes, it tries to interpret its findings with respect to both Social Disorganization Theory and these programs.

Project Exile

Project Exile was first implemented in the City of Richmond, VA in February 1997, and then was initiated in other American cities, such as Philadelphia, PA; Oakland, CA; Baton Rouge, LA; and Rochester, NY (Collins, 2002: 3). As such it is believed to have indispensable value as a crime policy program under the umbrella of "Project Safe Neighborhoods" as a nationwide program; Project Exile can be considered a local implementation of a nationwide crime policy program. Meanwhile, the primary objective of "Project Safe Neighborhoods" is to "enhance the penalties for gun crime by diverting those who have committed federal firearms offenses into federal court, where prison sentences are typically more severe than those found in most state systems" (Raphael and Ludwig, 2003: 2).

Until 1997, the City of Richmond had been primarily concerned about violent crimes before the Project Exile program was initiated (Rosenfeld, et. al, 2005: 424). This program, therefore, aimed to eliminate the high rate of gun violence and gun homicide by arresting and convicting individuals having an illegal firearm in the City of Richmond (Johnson et. al., 2001: 4). The main message of the program was "Project Exile: An Illegal Gun Gets You Five Years in Federal Prison." Although federal laws and regulations for firearms could be restricted to certain situations, the Project Exile program adopted federal regulations to ameliorate the epidemic of violent crimes in the City of Richmond (Collins, 2002: 5). Raphael and Ludwig (2003) agree that such enhancements on the length of prison sentences might potentially lessen the gun violence since this approach incapacitate individuals already convicted of gun related crimes, and therefore supposedly deterred crimes.

Another goal of the program is to enhance the collaborative efforts amongst local, state, and federal agencies. The program, therefore, establishes multi-agency collaboration, and brings the following agencies together; the U.S. Attorney's Office for the Eastern District of Virginia; the Richmond Police Department and Richmond Commonwealth's Attorney's Office; the Bureau of Alcohol, Tobacco and Firearms (BATF); the Federal Bureau of Investigation (FBI); the Virginia Attorney General's Office; and Virginia State Police (Johnson et. al., 2001:4).

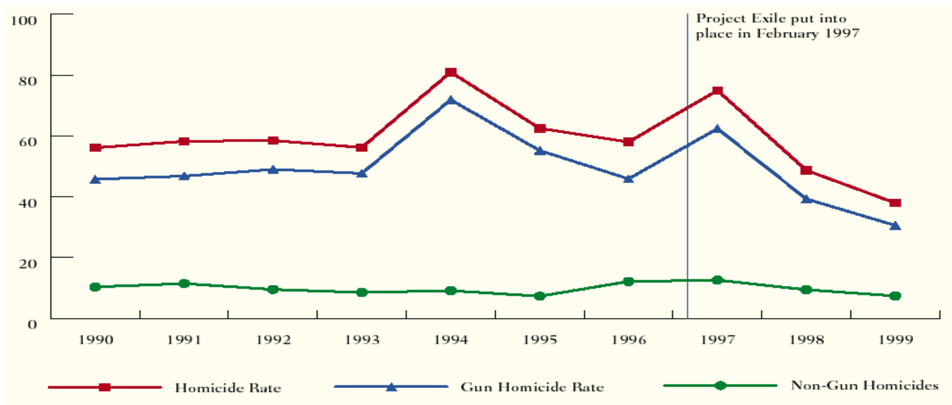
More importantly, Project Exile also aimed to improve the public awareness by promoting television, radio, billboard, and other advertising methods to convey its conclusive message. Further, it tried to encourage the inhabitants of the city to necessarily denounce illegal firearms to the Police. However, many researchers have not been able to find strong evidence claiming that the Project Exile was able to reduce violent crime rates overall (Raphael and Ludwig, 2003). Accordingly, Project Exile has been applied to develop both informal and formal social control. In fact, formal control refers to any implementations of both law enforcement and other responsible units in aiming to assert order and compel legal and regulatory codes (Kubrin and Weitzer, 2003: 381). Public awareness, on the other hand, should be evaluated in terms of improving informal social control from the perspective of Social Disorganization Theory.

Consequently, Project Exile did not specify any neighborhoods; rather, it was implemented citywide. Because of being a citywide program, the studies in the literature have not been able to compare the neighborhoods' crime trends according to whether the Project Exile was implemented or not (Rosenfeld, et al., 2005: 425). However, Project Exile has been assumed as the primary impact on the crime trends and patterns in the City of Richmond since 1997.

Although responsible officials continuously claim that it is heralded as an enormous success, only two empirical studies have been done in the literature so far. They were published by Raphael and Ludwig (2003), and Rosenfeld et al. (2005). These two studies find statistically little significant evidence for the impact of Project-Exile on homicide rates citywide. Both have done very good job to differentiate the impact of

Project-Exile on homicide/murder rates from the existing nationwide decline of homicide trends during their study period.

Figure 2.2: Homicide Trend in the City of Richmond from 1990 to 1999



Source: http://www.brookings.edu/dybdocroot/es/urban/publications/gunbook1.pdf

Nonetheless, much more empirical analyses are necessary to understand intended and unintended impacts of the Project-Exile in the City of Richmond. Project-Exile intentionally aims to reduce gun violence, but it might also result in some unintended outcomes as one considers its five central components together (Hamilton, 2004:1):

- Partnerships among federal, state, and local law enforcement officials against gun violence,
- Strategic plan for struggling with gun violence as accounting specific needs of community,
- Comprehensive training program for federal, state, and local law enforcement officers,
- Public outreach program and media campaign to increase public awareness of this program, and to make its deterrent message reach the community,
- Accountability to assess the program's success citywide.

Clearly, Project-Exile created very intensive atmosphere that makes community and officials be alert against gun violence. Project-Exile brings a longer mandatory federal prosecution for any crime escalated by gun, and Powerful media campaign especially enhances the anticipated public awareness about the Project-Exile (Raphael and Ludwig, 2003; DOCJS, 2003:5; Hamilton, 2004: 5). For instance, in their final report, DOCJS in Virginia (Department of Criminal Justice Service) recognizes the significant role of intensive media campaign exploiting television, radio, billboard, and posters with aggressive slogans on the buses. In fact, these buses were sent to different bus routes everyday during intensive campaign against gun violence. Therefore, they attempted to convey aggressive message of Project-Exile ("An illegal gun will get you five years in a federal prison") to the community.

Public Service Announcements were also dispatched to encourage the community to get across any illegal firearms in their neighborhoods to law enforcement ("Policy Evaluation of Exile", 2003). Literally, increasing the level of community awareness against such consequences might have increased community's calls for services, and, therefore, helped to control the crime rates in neighborhoods. Hamilton (2004) also addresses the role of community involvement to the success of Project-Exile. Notably, he specifically pays attentions on an increased collaboration from the minority community that had mostly questioned the police in the past (p. 6). Accordingly, such very concentrated environment across the city might also influence other types of crime rates rather than only gun-related crimes. In fact, offenders might change their strategy, and commit any other crimes not having firearm involved after the Exile.

However, it should be assumed that each neighborhood is treated with exactly the same dosage by such intensive citywide policy as one considers the program having modified federal legislation for local level felony. It is a citywide implementation, and no neighborhood grouping criteria. Although some neighborhoods might be very responsive to both intended and unintended impact of the Project-Exile, but others may not, no one can construct an experimental research design due to its citywide implication. In fact, its impact also remains constant in difference models. Nonetheless, this study acknowledges such citywide program, and attempts to interpret its findings in terms of both Social Disorganization Theory and the outcomes of Project Exile.

Blitz to Bloom

During the period between 1990 and 1999, the present study realizes another important policy program, which was implemented for only 30 days in 1999. It was an intensive police initiative implemented in certain neighborhoods. In fact, the Police Department started such a crackdown initiative in April 1999, and aimed at eliminating the crime in seven neighborhoods, called as "Bloom Neighborhoods" in the City of Richmond, VA (Smith, 2001: 60). It might be classified as short run crime control policy program. In literature, such policing activities have been frequently discussed by both practitioners and academic researchers. In his landmark study on police crackdowns, Sherman (1990) reports on how police crackdowns can reduce the crime rate if such policing could be implemented from one neighborhood to another. Adding that, police might get some advantages if such crackdowns could be intelligently rotated over time within the problematic areas of the city such as hotspots of crime distribution. Therefore, the strategies of “Blitz to Bloom” program include aggressive sanitization in the select neighborhoods, and prepare appropriate environment for civic associations and other city agencies to permanently recall social problems within the neighborhoods (Smith, 2001: 66). Accordingly, the police department implemented the “Blitz to Bloom” strategies in such seven problematic neighborhoods, and took 30 day police intervention in the City of Richmond.

However, a major issue of police crackdowns is that crime hotspots displace from one place to another due to the temporary effects of such policing interventions (Smith, 2001: 65). Robinson (2002) addresses three possible consequences of such policing at the neighborhood level such as subterfuge (Hiding and defending territories by offenders), replacement (Arresting, but replacing with new offenders), and displacement (movement from one place to another). Displacement, on the other hand, has been necessarily difficult to measure in the literature. Rationally, some researchers prefer to examine the hotspot movement in the neighborhoods adjacent to the targeted neighborhoods (Sherman and Rogan, 1995 cited by Smith, 2001:66).

Accordingly, this study acknowledges the cumulative impact of both “Project Exile” and “Blitz to Bloom”, and it examines neighborhood homicide changes in the City of Richmond over time. However; the main objective of the present study is not to evaluate these programs in terms their effectiveness or ineffectiveness. Rather, it benefits from the outcomes of these programs as it conveniently interprets the results in its conclusion.

Theoretical Background: Social Disorganization Theory

Overview

Criminological theories have distinguished between individual and structural characteristics (Paulsen and Robinson, 2004: Talon, 2004). Further, some studies prefer to integrate more than one theory to examine the context of crime occurrences. However, researchers have not always realized the additional benefit of theory integration (Cahill, 2004). Although theory integration might allow the researchers to work with various units of analysis from the individual level to the aggregated level, previous attempts at combining theories mostly ends in the rejection of one or more theories (Byrne and Sampson, 1986). Further, combining some theories might extend the scope of their studies; whereas a single choice of theory might help the researchers deepen their analyses with specific theory. However, Social Disorganization Theory itself can also be considered a theory that builds or combines other theoretical contemplations. Accordingly, this study prefers to examine only one theory to explain the spatial aspects of neighborhood homicide occurrences, and attempts to develop the operational definitions of Social Disorganization Theory (SDT) as exploring the context of neighborhood homicide.

As one of the most powerful structural theories, SDT becomes the main theory of the present study in explaining the associations between characteristics of neighborhoods and crime distributions over time. Studies on structural characteristics assume that something should be wrong in certain areas, and aim to answer the very basic questions such as what happens and why it is there (Paulsen and Robinson, 2004). In fact, structural studies primarily deal with environmental and social differences of criminogenic localities (neighborhoods) rather than individual differences amongst offenders and non-offenders (Roh, 2005). Such structural differences can, therefore, be spatially and non-spatially modeled based upon the SDT that allows characterizing the spatial composition of both crimes and neighborhoods. Both crimes and structural characteristics might actually become some part of social disorganization in neighborhoods. Social disorganization is like a process that brings these attributes together. And, Social Disorganization Theory lets the researchers investigate such processes in literature.

In fact, as a community-level theory, Social Disorganization Theory allows the researchers to examine the spatial variations of crime at the neighborhood level (Paulsen and Robinson, 2004: 53-73). More socially disorganized neighborhood might lead to less social control in the community (Sampson and Groves, 1989). Bursik and Grasmick (1993: 16-17) define social control as the neighborhoods protect public goods and services from other forces outside their communities. Conceptually speaking, people who cannot establish a cohesive link to their neighborhood (as shown by loss of social capital) might justify themselves in obtaining criminal capital, and are more likely to have tendency to commit crime within the same neighborhoods and/or others. In progress, criminal careers might apparently exist in certain zones as Shaw and McKay (1942) insist on their findings. To them, crime rates do not change in certain zones even if different neighbors move in/out there over time. Accordingly, neighborhood level findings seem critically important, and enhance neighborhood intelligence of both police organizations and crime policy makers.

From the ecologist point of views, it can be stated that structural findings might better guide crime policies at neighborhood level since citywide public policies might be better shaped by realizing contextual characteristics that influence crime patterns. These policies accept the cumulative impact of neighborhood characteristics on crime changes (Talon, 2004). That is, crime may dramatically increase in certain neighborhoods which have become more socially disorganized. This is because socially disorganized neighborhoods may not have a set of common values among the residents (Moriarty, 1999: 16). Loosing such adhesive components of the neighborhoods might lead to loose informal social control as well (Sampson and Groves, 1989). Accordingly, researchers might expect stronger relationships between contextual characteristics and crime at the neighborhood level (Rose and Clear 1996: 6).

Researchers studying SDT commonly characterize neighborhoods in terms of socio-economic composition, residential mobility, race/ethnic heterogeneity, urbanization, and family disruption. However, Shaw and McKay (1942) only utilized the first three structural characteristics, whereas Sampson and his colleagues added the rest two structural characteristics. These contextual characteristics, however, may not be considered enough without accounting for some intervening dimensions of socially organized community.

Sampson and Groves (1989) have, therefore, explored the mediating effects of community attachment and informal *social control*. These are the concepts of Hirshi's

Social Bonding Theory. Integration, social ties, and the mediating effects of both are the main intervening variables listed by Sampson and Groves as the contextual characteristics of neighborhoods. For instance, local friendships, volunteer organizations, and educational and recreational institutions might be strong mediators within the neighborhoods. According to their findings, such informal attachments within neighborhoods might enhance the collective efficacy. Hirschi's Social Bonding Theory also supports such social control in terms of having attachment, commitment, involvement, and belief in the society (Akers, 2000: 105-110).

Accordingly, Sampson and Groves (1989:777) cites from Bursik (1984: 31) "structural barriers impede development of the formal and informal ties that promote the ability to solve common problems. Social organization and social disorganization are thus seen as different ends of the same continuum with respect to systemic networks of community social control." Nonetheless, empirical studies have been limited to measure them as intervening variables (Sampson, et al., 2002: 458). Studies dealing with neighborhood institutions have utilized various crime occurrences as outcome measures, and found consistent findings in different cities. Their findings have motivated further studies with different approaches to explore how neighborhood mechanism influences on crime rates (Morenoff et al., 2001).

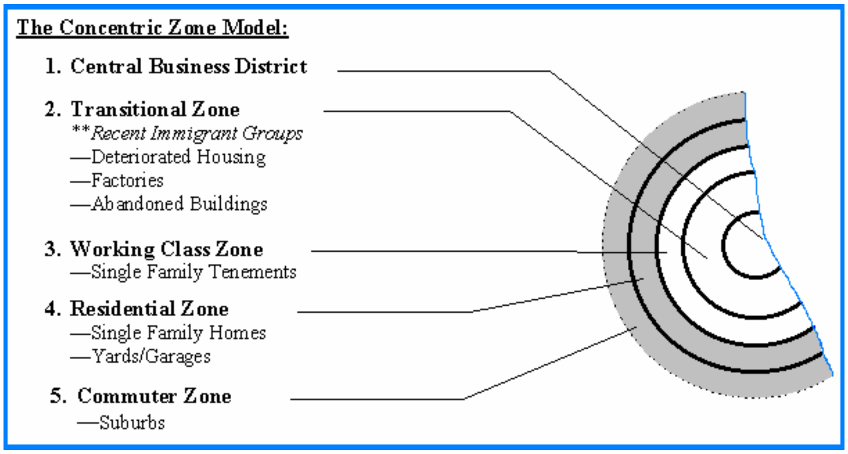
From the earliest studies of Shaw and McKay (1929) to the recent ones, the researchers have frequently focused on the crime variations in relation to neighborhood characteristics within the cities (Sampson, 1986). To enhance current policies and/or develop new strategies, policy makers and police managers should, therefore, realize the intersection of both change in neighborhood characteristics and crime variation over time.

Social Disorganization Theory From Past to Present

This section aims to extend the discussion of SDT above. It starts from the origin to the very recent approaches in the literature. It, therefore, covers many research studies, and reviews their conceptual and operational definitions in addition to their various research methods and findings.

Social disorganization theory emerged after environmental and social problems dramatically increased at the turn of twentieth century in Chicago (Paulsen and Robinson, 2004). As a result of changes of social and physical conditions, sociologists from the University of Chicago focused on the concept of social disorganization to explain why such conditions exist. Even conceptual framework of Social Disorganization Theory (SDT) lies upon the Durkheim, the social ecologists have applied SDT since Shaw and McKay (1929) designed a research study based on the "Concentric Zone Model" (Figure 2.3) that Park and Burgess (1925) developed to display the problematic areas in Chicago. In their model, the city was structurally characterized by five different zones such as "the central business district", "transition zone", "working-class zone", "residential zone", and commuter zone."

Figure 2.3: The Concentric Zone Model by Park and Burgess (1925)



Source: Retrived from http://faculty.ncwc.edu/TOConnor/301/301lect08.htm

As the central business district rapidly expanded, the transition zone was more likely to face continuous invasion of criminal activities. Consequently, such conflict reduced the degree of social control among people living in the transition zone. From the ecological perspective, the transition zone was shaped by the lack of social control, and was, therefore, imposed by higher social issues.

As a first study on Social Disorganization Theory, Shaw and McKay (1929) modeled such concentric zones, and proved that juvenile delinquency rates are not randomly distributed throughout the city. The highest rates of the delinquency were seen in the transition zone according to the concentric model. Further, the less delinquency rates were observed as the distance from the downtown increased. Evidently, their findings became congruent with the ones Park and Burgess (1925) explored the transition zone as problematic areas in the city. As a result, Shaw and McKay (1929) showed that poverty, racial/ethnic composition, and population turnover were the primary structural characteristics that might be related to high delinquency rates. These findings were originally considered as the first indicators of Social Disorganization Theory. Without of using any digital maps, they achieved a great success in their study. Today, spatial methodologies within GIS (Geographic Information Systems) environment might deliberately enhance the unit of analysis from the zone terminology to various aerial scales (Paulsen and Robinson, 2004).

Eventually, Social Disorganization Theory (SDT) has become the most important theory to explore the neighborhood characteristics and crime (Paulsen and Robinson, 2004; Sun et al., 2004). In their landmark study, Shaw and McKay (1942; 1969) examined, low economic status, residential mobility and racial/ethnic heterogeneity to measure social disorganization. Therefore, they developed a macro-social theory to address differences in these communities. Social disorganization provides the researchers with very flexible scope and depth in examining the structural characteristics of neighborhoods. That is, researchers find different ways to conceptualize and operationalize social disorganization (Moriarty, 1999: 15). In their well organized books, Paulsen and Robinson (2004) state the following neighborhood characteristics; population density, family poverty, employment, female headed households, vacancy rate of houses, own homes, residential mobility, public assistance (total households receiving public assistance), percentage of certain group (such as percentage of black people), business density, median income, crime rate (rate of crime levels per 1000 residents), etc.

On the other hand, some studies further examined the structural characteristics of neighborhood as utilizing some intervening variables for collective efficacy. The researchers contend that local institutions might promote social efficacy. The research on collective efficacy has primarily worked with structural dimensions of neighborhood such as social networks, institutions, residential stability, and informal social control (Curley, 2005). On the other hand, Sampson and Morenoff (1997) argue that structurally disorganized neighborhoods might lead to weaken the social cohesiveness within the community.

As mentioned earlier, Sampson and Grove (1989) extend the social disorganization theory by categorizing the variables such as exogenous and intervening ones. In fact, they state that urbanization, family disruption, socioeconomic status (SES), residential stability, and ethnic heterogeneity are considered exogenous variables. They further add some other variables to explore the intervening dimensions of social disorganization such as “a community to supervise and control teenage peer groups”, “local friendship networks”, and “local participation in formal and voluntary organizations” (Sampson and Grove, 1989). They employed multivariate regression and path analysis to examine the direct and indirect effects of neighborhood characteristics on crime rates. They address that higher crime rates are observed within the neighborhoods where friendship networks are weaker; local participation is low; and community cannot supervise the teenage groups well.

However, they did not argue that these intervening variables fully mediate the socially disorganized communities (Lowenkamp et al., 2003: 365). Sampson and Groves basically employed weighted least squares (WLS) to regress these intervening variables on each exogenous variable. They ultimately obtained moderate level regression models as considering the associations between crime variation and structural characteristics. Although WLS could do very good job for their studies, they would had better perform spatially weighted regression in 238 neighborhoods, and make sure about spatial dependency within their eight different models.

They empirically found very cohesive relations amongst victimization, family disruption, and urbanization. Residential stability, in their findings, was found directly related to local friendship networks. As residential community becomes more stable, local friendship networks are more likely to increase (Sampson and Grove, 1989). Having said that, the general hypothesis of their study is that low economic status, ethnic heterogeneity, residential mobility, and family disruption might be primary factors for community social disorganization. To them, socially disorganized communities might lead to raise the level of crime rates and delinquency. They tested their model and explored solid findings to support their developed version of social disorganization concept. They realized that both exogenous variables and intervening variables together can further explain the variations in crime rates. Veysey and Messner (1999) later retested the same hypotheses that Sampson and Grove stated in their studies, but they employed Structural Equation Modeling instead of Multiple Regressions with WLS. They explored some mediating factors in relating low socioeconomic status, residential mobility, and racial heterogeneity with crime rates. They could not address the same impact on the relation between crime rates and family disruption.

However, even if Sampson and Groves (1989), Shaw and McKay (1942), and Bursik & Grasmick (1993) similarly approach to the structural factors and address possible associations of these factors with crime rates, social disorganization should not be considered as direct cause for crime variation at neighborhood levels. Further, it is recommended to say that the variables of social disorganizations refer to disrupt the *social control* within the society and neighborhood, and such loosen social controls prepare appropriate environment leading to higher crime rates. Accordingly, social disorganization indirectly influences the crime variations within the neighborhoods.

As one of the most well known social ecologists who recently improved the social disorganization theory since 1980s, Sampson (2002) has been primarily focusing on social control facets of social disorganization. Also, Cahill (2004: 22-23) posits that structural facets of disorganization are relevant to explore the aggregated variations within urban violent crime, such as neighborhoods. In fact, the existing of such structural characteristics (low SES, high residential mobility, high racial and ethnic heterogeneity, and family disruption) might result in higher social disorganization, and increasing the opportunity structure for criminal activities (Elliott et al., 1996: 394).

Recently, Lowenkamp et al. (2003) replicated such extended version of SDT, and showed the consistency of Sampson and Grove's criminological classic. Lowenkamp and his collogues (2003: 353) confirmed empirical findings of Social Disorganization Theory, and proved that SDT should still be considered as a solid theory to examine macro-level crime variation across the time and place within neighborhoods. Their study was completed within 238 British communities, and their individual level data was aggregated to contextual level. They operationalized exactly the same structural variables, including SES, residential stability, ethnic heterogeneity, family disruption, and urbanization.

Although Lowenkamp and his collogues conducted Hierarchical Linear Modeling (HLM) different than previous researchers performed, they precluded its inquiry because some types of neighborhood units did not provide enough sample sizes to assess the structural data within HLM (p.356). Then, they utilized LISREL software to build structural equation modeling to explore mediating impact of some structural variables. Their findings have become consistent with what Sampson and Grove (1989) obtained. While Sampson and Grove worked with the British Crime Survey conducted in 1982, Lowenkamp and his Colloquies (2003) replicated SDT with the 1994 British Crime Survey. Accordingly, structural characteristics and intervening variables of social disorganization have been directly tested by the social ecologists, and confirmed SDT as an appropriate theory to examine the crime distribution at macro-levels.

Sun and his colleagues (2004: 1-16) also directly tested Sampson and Groves' Model of Social disorganization, and their findings supported the results Sampson and Groves obtained. Different than previous studies, Sun and his colleagues concentrated on two types of crime such as assault and robbery. They, therefore, report that structural characteristics of neighborhoods influence assault much more than robbery. In data collection procedure, they conducted interviews with 8155 individuals who were randomly selected from 36 neighborhoods in seven different U.S. cities, including Houston (TX), Baltimore (MD), Newark (NJ), Madison (WI), Oakland (CA), Denver (CO), and Birmingham (AL). In their study, they define neighborhoods in regard various ecological units such census tracts, census block groups, and police beat boundaries for each cities. Then, they aggregated these individual level data to the neighborhood level.

They utilized the same exogenous variables as neighborhood structural characteristics (SES, residential mobility, racial heterogeneity, and family disruption), and intervening variables (local social ties, organizational participation, and unsupervised teenage groups). Their findings fully support the mediating factors of local social ties on crime rates, but partially confirm the mediating impacts of both organizational participation and unsupervised teenage on crime. However, they argue that these two intervening variables have still played significant role to enhance informal social control within neighborhoods.

The present study, therefore, examines the neighborhood level homicide as dependent variable in relation to structural characteristics. Nonetheless, the study retests an almost complete form of Social Disorganization Theory except its intervening dimension in the city Richmond. However, it attempts to retest SDT with difference models to explore possible associations between the change in neighborhood social disorganization and the change in neighborhood homicide over time. It, therefore, becomes a unique study as this research investigates the consistency of SDT with difference models.

Accordingly, the present study realizes suitable concepts of social disorganization theory to characterize the context of neighborhoods. It firstly confirms potential associations between homicide variation and neighborhood configurations. Then, it attempts to design longitudinal research to explore the change in neighborhood composition as detecting possible crime pattern change over time. SDT is, therefore, more likely to allow the present study to determine how much variation and/or what probability of having neighborhood homicide might be explained by the change in neighborhood disorganization.

Select Studies on Homicide in Relation to Structural Context

This study primarily focuses on the homicide, which is known as the most problematic crime in the City of Richmond (Rosenfeld et al., 2005). The selected literature on the homicide in relation to structural context eventually assists the research extensively compare its findings with previous academic efforts and interpret them for active policy considerations.

Literature covers many studies about homicide in relation to structural context. These studies are primarily distinguished from each other with respect to how they examine homicide distribution for intra city and/or inter cities. Interestingly enough, most of the studies have been completed for inter cities considerations. In fact, they have basically compared various cities across the U.S while they use cities/states/regions as their unit of analyses in their studies. Nonetheless, few research studies have worked for intra (inner)-city settings as they analyze structural context in relation to homicide. One reason to neglect intra-city approaches for homicide would be because of homicide itself as a very rare event in the cities as compared to other crimes. That is, many neighborhoods might have only one homicide in the entire year, even zeros in many other neighborhoods.

Such unique characteristics of homicide might especially become more problematic in longitudinal research settings. Previous studies, for this reason, have preferred to aggregate homicide incidents into county/city/state/region levels to broadly work for inter cities. Wilson (1987: 46-62), however, contends the idea of "concentration effects" as he examines the community level indicators in relation to criminogenic areas in the cities. Wilson, therefore, recommends concentrated disadvantages to work inner city for the purpose of exploring possible associations between neighborhoods' structural characteristics and crime variation. As this unique research deals with these methodological and conceptual issues, it brings the select studies together, particularly related to both structural context and homicide in the following literature.

Land and her research team (1990) compared cities, metropolitan areas, and states in U.S. as they explored structural covariates associated with homicide rates. Their concern was about empirically inconsistent results showing the association between homicide and structural characteristics in the literature. Considering different time periods and locations, they expected various degrees of cultural settings and social disorganizations in these locations. Although they used the idea of informal social control to investigate structural context of homicide, they broadly aggregated homicide incidents into such geography. They borrowed the same conceptualization from Shaw and McKay (1942), Kornhauser (1978), and Sampson (1987). In fact, weakening level of informal social control has been the promise for them to explain higher deviance and crimes such as homicide.

Land et al. (1990: 931), therefore, utilized the following structural covariates extracted from Census data as explanatory variables: population size, population density, percentage of the black population, percentage of the population ages from 15 to 29, percentage of the population of males ages 15 and over, divorced families, percentage of the children 18 years old or younger not living with both parents, median family income, percentage of families living below the official poverty line, Gini index of family income inequality, the unemployment rate, and a dummy variable showing where these cities, metropolitan areas, or states are geographically located in Southern U.S. They worked with three different decennial census years such as 1960, 1970, and 1980. They run and estimated the same regression model for different census year. Therefore, their studies without change process may not be considered a longitudinal research over time. That is, they constructed their model, and tested at separately single time step with the manner of cross sectional approach.

Methodologically, Land and her colleagues (1990) initially run their multiple regression models with 11 covariates above, and they realized that their regression models were inconsistently performed from one census year to another. Then, they utilized principle components to reduce the number of covariates, and avoid from multicollinearity threats in their regression models. Ultimately, their respecified baseline model revealed consistent findings from 1960 to 1980. In their revised model, they obtained two main components such as a population structure component, and a resource deprivation/affluence component. Specifically, the second component is consistent with Wilson's (1987) perspective of concentrated effects. Ultimately, they constructed their revised model with six structural index and covariates such as population structure, resource deprivation/affluence, percentage divorced, percentage ages 15-29, unemployment rate, and south.

In their findings, Land et al. (1990: 932) report that resource deprivation/affluence index had the strongest influence in each subsequent census years. Percentage divorced as a social disorganization indicator proved strongly positive relation with homicide rate at city, state, and region level. Population density and the percentage of divorced male population also showed positively strong relationship with homicide rates. However, unemployment rate, and population ages 15-29 did not show evidence for the association with homicide rates. Clearly, homicide rates at city and/or state level may provide enough variation for the OLS (Ordinary Least Square) to fit the models, and supports the structural theories. The present study, on the other hand, suffers from homicide as a rare event since it does not allow the research to construct multiple regression models with OLS at neighborhood level. This study, therefore, need to come up with a solid statistical approach to model the homicide with respect to structural covariates at neighborhood level.

Krivo and Peterson (2000) have also studied structural context of homicide, but more focused on racial differences at city level across the nation. They wanted to explore whether white or black population does matter to explain the homicide in relation to structural context. More specifically, they examined homicide rates for the cities where African Americans lived in some degree (at least 5000 black persons living). Another criterion was to be Metropolitan Statistical Area central cities with a population at least 100,000. They, therefore initially obtained 135 cities to meet their selection criteria for year 1990. Since some cities did not have homicide data, and some presented outliers among them, their final sample size only included 124 central cities for the purpose of their studies. They used homicide rate as dependent variable with natural logarithm transformation while they utilized concentrated disadvantage, community stability, racial residential segregation, and interracial socio-economic inequality as independent variables in their model. Nonetheless, they calculate the average of 1989-1991 years to minimize the impact of year differences in homicides as they study cross-sectional level. Notably, their primary purpose was to differentiate the effects of their theoretical predictors between two racial groups such as whites and blacks. In their analyses, their major problem was related to heteroskedasticity because of various cities included. They, therefore, performed weighted-least-square (WLS) regressions such that error variance was specified with inverse function of population size for the blacks.

In their findings, Krivo and Peterson (2000) realized significant differences between these two racial groups as they explore the variation within homicide rates in relation to structural covariates in U.S. cities. Interestingly, concentrated disadvantage was not a significant indicator for African American population as they explore the homicide rate variation for blacks. Krivo and Peterson (2000: 556), therefore, result that "criminal violence should not be systematically associated with the variation in structural conditions for African Americans." On the contrary, their findings have become more consistent with theoretical results for the white population. Accordingly, structural predictors of homicide rates might be moderately weaker in socially disadvantaged cities. Another important result would be that such significant differences between white and black population in socially disadvantage cities might also indicate various effects in different portions of disadvantage across the cities. To them, if black and white populations show similar portions in cities, then they might be comparable to each with respect to criminal violence such as homicide.

Lance and College (2005) specifically focused on the association between homicide rate and extremely poor neighborhoods in New York City. Again, they constructed a cross-sectional research design for the census tracts, as the proxies of neighborhoods. Although there are initially 2,042 tracts, their research was established on sub-sample of these tracts to meet extremely poor neighborhoods. They ultimately obtained 227 neighborhoods as their final sample size. The authors used homicide victimization data gathered from the New York City Coroner's office, then geocoded their street level addresses in GIS. Then, they aggregated these geocoded homicide victim data into census tracts. Since they use the 1990 Census data to operationalize socio-economic composition of neighborhoods, they averaged census tract level homicide data for the years 1988-1994. Although Lance and College (2005) used seven years homicide data to minimize the fluctuations around the Census year 1990, such a large range might have also caused misinterpretations in some degree.

In their structural variables, community disadvantage index, divorce rate, residential stability, structural density, vacant houses, percent ages 15-34, sex ratio, and African-American Tracts have used as independent variables in their model. More specifically, the disadvantage index was operationalized by combining four highly correlated structural variables such as poverty rate, median family income (reverse coded), the percentage of households receiving public assistance income, and the percentage of female headed household families. Other structural variables were also derived from the Census 1990 data.

Lance and College (2005) operationalized extremely poor neighborhoods with respect to the poverty rates 40 percent of more. In fact, they classified all census tracts (as proxy of neighborhoods) into three different groups such as tracts with poverty rates less than 20%, the tracts with poverty rates between 20% and 39%, and the ones with poverty rates 40% and greater. In the line of such classification, they established a framework so as to assess various effects of structural covariates on homicide rates at various types of neighborhoods. In these specially selected neighborhoods, the degree of neighborhood disadvantages was positively related to homicide rates. In fact, the association between social disadvantage and homicide rates shows significant findings in such extremely poor neighborhoods, more specifically in African-American neighborhoods. Clearly, their results remained consistent with what Wilson (1987) explored the inner city concentrated disadvantaged neighborhoods in his landmark study.

Lance and College (2005) performed Moran's I statistics to assess the spatial autocorrelation among the neighborhoods. Therefore, they contend that high crime rate neighborhood is more likely to exist in certain ones that are contagious to these neighborhoods with high homicide. That is, socially disorganized neighborhoods might also impact the degree of social disorganization and/or violence in adjacent neighborhoods. Global Moran's I statistics proved a positive spatial autocorrelation in NYC census tract homicide rates. Meaning that, neighborhoods with high homicide rates are surrounded by the ones with high homicide rates, whereas the neighborhoods with low homicide rates are spread around the ones with low homicide rates. Sensibly, Lance and College (2005: 1427) attempted to validate their results by including spatial lag term as a control variable, and aimed to perform more robust models.

However, adding only spatial lag term as a control variable may not actually capture the spatial dependency across the neighborhoods in OLS models since they wouldn't be able to construct full spatial regression model with MLE (Maximum Likelihood Estimation). In fact, spatial regression model might be either spatial lag model with dependent variable, or spatial error model with independent variables (Anselin, 1988). Even sometimes, combined spatial regression models might be necessary for the robustness. Since they did not investigate either of them, their spatial lag addition to traditional OLS model may not have appropriately fixed the spatial autocorrelation in the model. This decision should be considered trade off between actual spatial autocorrelation with complex models and the sake of simplicity for the purpose of their study.

Messner et al. (1999) have studied with aggregate level homicide data across the counties as they examined the homicide distribution for two different time periods such as 1984-1988 and 1988-1993. In fact, they only worked with the counties in St. Louis metropolitan area. They particularly investigated diffusion process between these periods. Their findings show that homicides are not randomly distributed over these years. The changes in the distribution posit some diffusion from one county to another, especially to nearby counties over time. Although they realized positive spatial dependency for each time steps, first period barely showed changes, and became more static as opposed to second period. More specifically, they found statistical evidence on how more affluent areas and more rural areas stay away from homicide diffusion and distribution over time.

In their research methodology, Messner et al. (1999: 428) report a number of reasons why they preferred counties to examine spatial distribution of homicide data. First, counties are the most common unit of analysis for data collection since a variety of official records keeps invaluable diverse information at county level over time. In fact, social-economic, demographic, political data might be accessible for the researchers. Second, counties, different than MSAs and metropolitan cities, might provide a better range of social landscapes from rural to more dense areas. That is, researchers might compare them in terms of whether rural or urban areas. Finally, Messner et al. (1999) argue that recent literature has better supported structural covariates to explore homicide distribution at the county level.

Although Messner et al. (1999) suggest several reasons to use counties as unit of analyses; this approach might have some constraints. First, county geography might not capture the actual diffusion process at appropriate ecological scale, since they are just administrative units. For instance, some of the counties might include very heterogeneous populations. Plausibly, diffusion process may not be captured for short distances between the counties with more heterogeneous populations. More deeply, homicide rates may not remain stable in these counties. That is, the dissertation project deals with such instable population for smaller unit of analyses such as neighborhoods in the City of Richmond. Then, homicide rates and/or counts have become very rare events at neighborhood level.

Messner et al. (1999: 431) selected various structural covariates consistent with what Land et al. (1990) as they extracted both 1980 and 1990 census decennial information for the purpose of their studies. Structural variables include population, population density, percentage black, percentage of families below poverty, percentage civilian labor force that is unemployed, median family income, Gini index of family inequality, percentage of the population aged 15-29, percentage of males aged 15 and over divorced, and the percentage of family households with own children present with a spouse absent. Similar to Land et al. (1990), Messner et al. (1999) performed several principle component analyses to establish some composite variables to avoid from both multicollinearity and instable findings over time. These structural components consist of a population structure component and a resource deprivation component.

In their findings, Messner et al. (1999) have drawn significant results. First, hypothesis about spatial randomness is evidently rejected. That is, statistically significant hotspots and cold spots of homicide rates are observed in the metropolitan area. Second, local patterns of both hotspots and cold spots showed some diffusion process over time. That is they called as contiguous diffusion process of homicide rates over time. Third, their analyses for the structural covariates in relation to homicide have also become consistent with previous county level researches. That is, homicide rates are likely to change in various counties that might represent various structural contexts. Finally, they identified some obstacles to homicide diffusion from one county to another over time. In fact, the ones with rural and agricultural characteristics did not show high homicide rates even they are surrounded with high homicide rates. Further, least deprived counties have not been diffused by high homicide rates over time.

Clearly, researchers have preferred to utilize higher level aggregation so as to study with conveniently large, and non-zero events at some ecological scales. Homicide, therefore, would be considered continuous variables to run spatial regression models at large ecological scales. Otherwise, conventional spatial regression techniques cannot be studied with very rare events or non-linear distribution of these incidents. In fact, with count data (for instance homicide incidents per neighborhoods), one may not use OLS or its spatial regression alternatives (spatial lag, spatial error, or combined robust models) when dependent variable is much skewed for such rare events. Then, researchers need to come with different approaches as Lance and College (2005) has added spatial lag term of DV into the model, and run conventional multivariate statistical techniques rather than spatial regression analytics.

On the other hand, studying with only county or higher level aggregated crime data may not thoroughly address the policy issues at lower scales such as neighborhoods. Otherwise, they are more likely to be fallen into ecological fallacy such that they would attempt to explain micro level variation by macro level changes. Accordingly, there is more need to study homicides at neighborhoods across the cities. The present research further enhances such existing gaps in some degree, and expands the literature by exploring whether the change in homicide is significantly associated with the change in neighborhood social disorganization over time.

Scope and Depth of Present Study

The present study determines its scope and depth in terms of following components; neighborhood crime (e.g., homicide), Social Disorganization Theory, various policy programs, and crime trend/pattern changes.

This study identifies socially disorganized neighborhoods as it detects pattern changes in homicide over time. That is, the scope of the present study focuses on homicide as a violent crime instead of all types of neighborhood level crimes. The scope is limited to Social Disorganization Theory instead of combining more theories. This study, however, gives particular attention on homicide distribution, which has been the most questionable crime in the City of Richmond. As thoroughly analyzing the homicide data, it deals with the unique characteristics of homicide data such as rareness, and its much skewed distribution.

Rather than having static crime distribution over time, the present study anticipates that crime distributions will necessarily vary from one time step to another as the variation might be attributed to the change in neighborhood disorganization. In fact, spatial distribution of crime pattern might vary from one place to another due to the neighborhood changes. Then, the question becomes what is the role of neighborhoods in explaining such crime variation over time? The present study, however, acknowledges the possible impacts of policy implications in the City of Richmond between 1990 and 1999. The findings of this study are, therefore, interpreted in terms of both social disorganization theory and various policy implications together.

This study will utilize multiple time steps to enhance the longitudinal analysis, and to get the complete picture as homicide has changed over time by examining short term and long term changes in social disorganization in the City of Richmond, VA. More specifically, the main purpose of this study is to explore whether the change in social disorganization can explain the change in homicide over time.

Chapter 3

Research Design and Analytical Methodology

Overview

The research has reviewed *what* it wants to accomplish as it establishes conceptual level research components so far. Now, this section frames the elements of a solid research design and analytical methodologies so as to illustrate *how* this study can accomplish its objectives. The present study uses *quantitative research* methodology, constructs a longitudinal research design, and employs *secondary data analysis* to test the hypotheses. The main hypothesis for the purpose of this study is "Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time." Again, definition of neighborhood crime is limited to only homicide due to the limited crime data availability in this study. The present study, however, is supposed to test five traditional hypotheses constructed by the social disorganization theory before testing the main hypothesis. In addition to these five disorganization indicators, this study also constructs two more testable hypotheses for "Youth" and "Vacancy" as identified other neighborhood disorganization indicators. On the other hand, dummy variables for policy programs are included as control variables in the models.

Accordingly, this chapter aims to establish a comprehensive and analytical mechanism as it fulfils its reasonable objectives. Systematically, this chapter consists of the following components: Research questions, methodological assumptions, strategy of the research methodology, Secondary Data Sources and Analysis, Research Design, Analytical Techniques, Validity & Reliability Issues, and Limitations of the Study.

Research Questions

- Is neighborhood homicide associated with social disorganization?
- Which elements of social disorganization have the largest impact on neighborhood homicide variation?
- Does the change in neighborhood social disorganization explain the change in neighborhood homicide over time?

Methodological Assumptions

The present study derives some assumptions so as to measure possible association between the change in neighborhood social disorganization and the change in neighborhood homicide over time. These are:

- Each neighborhood (like census block groups) has unique characteristics in each Census year, but they are different from each other in the city. Also, characteristics of each neighborhood might have varied from one census year to another.
- Socially disorganized characteristics lead to less *social control* in the neighborhoods according to the previous studies' findings in the Social Disorganization Theory (SDT) literature. Exogenous variables of Social Disorganization Theory are more likely to confound the level of such informal social control in the neighborhoods. Ultimately, as contextual

characteristics vary over time, the level of crime rates might also respectively change in the neighborhoods.

Strategy of Research Methodology

The present research states its methodological strategies in three subsequent phases.

- First, it examines the SDT variables for each separate year from 1990 to 1999, compares these variables, and realizes the consistency of SDT as the degree of neighborhood social disorganization varies over time in the same city. In this phase, this study, primarily, retests the primary hypotheses of SDT.
- Second, it calculates the differences for both neighborhood homicide and values of neighborhood social disorganization with respect to SDT, runs difference models to explore whether the change in neighborhood social disorganization can explain the neighborhood homicide variation over time.
- Last, it establishes multiple regressions model for only neighborhoods experiencing homicide incidents hotspot(s) over ten years from 1990 to 1999. This study, therefore, would be able to narrow down the most problematic neighborhoods for the policy consideration.

As seen in the conceptual model of the present study, change in neighborhood disorganization is used to capture the change in neighborhood homicide (as an example of neighborhood crime) by various statistical models using difference values for both neighborhood homicide and social disorganization attributes. At this level, this study identifies the specific neighborhoods which might have unusual neighborhood homicide variation over time as it accounts the factors of Social Disorganization Theory. To remind, the more socially disorganized neighborhoods the more crime. In fact, this study only uses the contextual variation in the neighborhoods as it explains the variation of neighborhood homicide over time. Again, the main focus of the present study is social disorganization to capture such variation in neighborhood homicide. This study, therefore, anticipates that various neighborhood homicide patterns over time might be because of the variability within structural neighborhood characteristics (only social disorganization). Difference models constructed by various regression models allow the research to test its main hypothesis. In this approach, dependent variable is treated as the neighborhood homicide change, whereas IVs are recalculated by the changes in values of neighborhood social disorganization (Seven different covariates at neighborhood level) in the conceptual model. Accordingly, the main hypothesis of this study is tested by whether there exists an association between change in neighborhood homicide (between 1990 and 1999) and the change in neighborhood social disorganization. Ultimately, the multiple regressions model for specific neighborhoods having homicide incidents hotpot(s) will finalize the findings of the present research.

This study attempts to achieve its objectives in the City of Richmond, Virginia as a case study. In terms of its purposes, this study is not limited to specific working area. Any city in the world can be studied by this approach. However, the City of Richmond has some unique characteristics with respect to the various policy programs implemented in the study period of time. And, homicide has been the most questionable violent crime in the City of Richmond so far. Consequently, the findings might become more prudently interpreted by the elements of programs and the factors of Social Disorganization Theory together.

Secondary Data Sources and Analysis

Secondary data analysis requires examining major sources of data to test the hypotheses derived by the research studies (Nachimias and Nachimias, 2000). The major source of secondary data includes the Census, special surveys, archival data, UCR/NIBRS, and the Internet. Conceptually, secondary data is the only data that can possibly be used in certain research problems. Therefore, it would be a good entry point to address social issues. Methodologically, it offers some advantages, such as opportunity for replication, reliable and accurate data, availability of data at different time date scales, and the ability to improve the validity of measurement. Lastly, it is comparably inexpensive to utilize existing data as opposed to collecting original data. Accordingly, these relative advantages of using secondary data are why the present study determines to process its research mechanism based on secondary data. Some limitations might, however, exist for using secondary data in terms of testing hypotheses, accessibility to data, and insufficient information (Nachimias and Nachimias, 2000).

The present research, therefore, employs various secondary data as data sources including the Census and crime database of the Police Department with UCR (Uniform Crime Reports) format for the period of study. These data are, then, repeatedly processed for different purposes within the study. Nonetheless, each dataset might have some shortcomings as explained below.

Empirical analysis of this study is conducted with census block group level (proxy of the neighborhoods) in the Census hierarchical geography (Figure 2.1). As one of the deficiency of secondary data, Census 1990 geography is not completely coincided with Census 2000 geography. This study, therefore, makes critical decision on fixing this problem and becoming ready for a longitudinal research (See Appendix A).

In terms of neighborhood homicides provided by the Police Department, this study needs to be careful about their address spellings and typos as it geocodes them by their incident address information, and correctly assign x/y geographic coordinates for each neighborhood homicide incident. Since this study has no sense about who recorded these crimes and in what conditions were recorded, it has no control for the quality of crime records with respect to misspellings and missing information. Fortunately, the present study only deals with index type of crime (e.g., homicide) with UCR format, and rely upon the very standard and consistent data recording procedures designed by FBI (Federal Bureau of Investigation). And the Police Departments have to strictly follow up these procedures.

Homicide incidents data is provided by Richmond Polis Department for the years from 1990 to 1999. The reason for this period is obtain a consistent and comparable crime data set over time. In fact, UCR and NIBRS crime data sets are not compatible in the City of Richmond after 1999. This becomes an obstacle to establish longer time steps for the longitudinal research.

Census 1990 and Census 2000

The census data is one of the most comprehensive secondary data sets and are gathered by the government for policy and administration needs (Nachmias and Nachmias, 2000). The Census dataset provides this study with economic and demographic indicators of the locations in the City of Richmond, Virginia. More specifically, the census data consists of household structure, income distribution, immigration and migration patterns, characteristics of racial and ethnic groups, environmental changes, attributes of rural and urban areas, and more about the neighborhood characteristics in the Census geography (Census blocks groups). Census data for 1990 and 2000 actually provides standard definitions for all structural covariates employed in this study. They, therefore, allow the researcher to perform appropriate measurements with the consistency of both conceptual and operational definitions of structural covariates. The study specifically extracts the Census data for all the census block groups within the working area. Accordingly, this study establishes a comprehensive dataset that includes neighborhood characteristics based upon the Social Disorganization Theory such as SES, residential mobility, racial/ethnic heterogeneity, family disruption, population density, youth, and vacancy.

However, Census 1990 is quietly different than Census 2000 in terms of block group geography. In fact, the number of census block groups is not equal to the ones of Census 2000. The present study, therefore, has to make these two different Census geographies at bock group level compatible to each other. Otherwise, it cannot compare these two years, and cannot establish difference models over time. The present study has found two solutions to compensate such issues in the research. One is to utilize the best approximations with census blocks, which are much smaller than census block groups. It can make some estimation so as to use census 1990 data for the geography of census 2000. Another solution, on the other hand, is to purchase such compatible data from some vendors which closely work with Census Bureau. First way consumes too much time on processing these data, whereas the second way costs some money. The study, therefore, decides to purchase Census 1990 data and geography normalized to Census 2000 geography (See Appendix A).

This study uses 1999 as the last time step for the working period of time since Census 2000 data were actually gathered in 1999, and distributed in 2000. It, therefore, uses 1990 and 1999 as the edging years while it runs the linear interpolation to calculate the remaining years between them.

Crime Database of Police Department

The present study requires incident level data for ten years of period between 1990 and 1999. It limits itself to have a compatible crime data with Uniform Crime Report (UCR) format over the years. Otherwise, UCR and National Incident Based Reporting System (NIBRS) are not compatible to each other over the years. This study, therefore, only needs addresses of the incidents, type of crime, and date of incidents for the purpose of the research. Once the crime data are obtained from the Police Department, this study firstly performs geocoding to assign individual point for each incident, then spatially aggregates them into census block group levels (as the proxy of neighborhood) in GIS environment. That is why this study calls neighborhood homicide after aggregating the individual homicide incidents to the neighborhood level. In fact, the Police Department does not provide the crime data at census block group level. The present study, therefore, has to process the incident level data to aggregate into the census block groups as unit of analysis in this research. Incident level data are also necessary to generate crime hotspots in GIS for the last phase of the study.

Research Design

This section covers four areas: type of research design, unit of analysis, measurement of variables, and hypotheses. The present study constructs a longitudinal research design with trend data for neighborhood compositions and crime. This section, therefore, discusses why it is necessary to conduct such specific research design, and argues primary justifications for each variable in the conceptual model.

Longitudinal Research Design

This research employs a longitudinal research design. Longitudinal research allows examining certain data gathered at many time periods. Longitudinal designs are, therefore, suitable for both descriptive and explanatory research purposes (Neuman & Wiegand, 2000). Generally speaking, this type of design might delineate the patterns of change in the research subjects over time, and, more specifically, measure the variations within dependent variable from one period to another. Therefore, it might be applied to explore the root causes of social issues (Menard, 1991:5).

In longitudinal research design, the same cases (like neighborhoods) are repeatedly examined over certain periods of time (McMillan, 2004:197). In this line of reasoning, longitudinal approaches allow this research to capture the change within the neighborhood social disorganization and neighborhood homicide over 10 years. Longitudinal research, therefore, is suitable choice for both accomplishing the purpose of this study and examining the complex social problems (e.g. community level questions) and the issues such that cross-sectional design can not deal with.

Menard (1991:4) defines the term “longitudinal” with respect to three different perspectives. One is that longitudinal data requires *two or more time waves* for each variable (e.g. neighborhood social disorganization variables and homicide) or item in the research. Second, research subjects (like neighborhoods in this study) should be the same, or, at the bottom line, should be comparable to each over time. Last, longitudinal analysis is likely to include multiple comparisons of the research subjects between two or more time waves. This study uses such data at many time steps (e.g., 10 years) for both neighborhood social disorganization and homicide as it constructs individual model for each year, difference models for subsequent year ranges, and a model for the entire period (to investigate the changes of both homicide and neighborhood social disorganization within / between neighborhoods over years). In fact, this study constructs many difference models according to the peak points (distinguished changes over the 10 years periods) realized in the plot of homicide rate trend from 1990 to 1999 (Figure 4.8). Such data for ten years allow this research to determine the *net changes* at the aggregate level (e.g., neighborhood level). This longitudinal approach, therefore, resolves the time related consequences in cross-sectional and correlational research designs. Fortunately, since such a research design can easily work with secondary data, it is commonly preferred to save time, money, and personnel to complete a longitudinal research design (Trochim, 2000).

Such kind of longitudinal study can also provide very comprehensive framework to reveal possible influences of various events (e.g., Project Exile and Blitz-to-Bloom Programs) on the subject. That is, external validity might become higher than cross-sectional research designs. Accordingly, the present study attempts to explore the association between neighborhood social disorganization and neighborhood homicide variation over time. The design, in this study, is strictly guided by Social Disorganization Theory, and, therefore, statistically controls for confounding predictors of neighborhood crime changes over the years.

Longitudinal study, on the other hand, might lead to some internal validity issues if the researcher wants to reveal causal-effect relationships (Menard, 1991). Although the present study does not look at the causal-effect relationships between neighborhood social disorganization and neighborhood homicide variation over time, it covers the time order condition (From 1990 to 1999) and covariation between predictors. Rather, it investigates the *association* between the change in neighborhood social disorganization and the change in neighborhood homicide. Therefore, the present study expects to minimize the possible threats against the internal validity in its longitudinal research design with 10 year dataset.

In addition, this study utilizes the entire population of the working area instead of establishing any sampling procedure. Working with the population might also possibly reduce the possible threats against internal validity in a longitudinal research design since the significance level becomes irrelevant, and the results just reflect the reality in this study.

Accordingly, such preferences in this study are more likely to assure about the possible methodological limitations of longitudinal research design with 10 years neighborhood homicide and social disorganization data.

Unit of Analyses

The present study utilizes census block groups (proxies of the neighborhoods) and incident location as the unit of analysis. Although census blocks are the smallest geographic units, the census does not allow the researchers to access detailed neighborhood characteristics at the census block level. Even if we could access the data, census blocks might provide very homogeneous areas with the investigation. They might hardly allow exploring the variation within neighborhood homicide in relation to the degree of neighborhood social disorganization. Further, the census block groups provide the researchers with comprehensively detailed neighborhood characteristics in terms of low SES, residential mobility, racial/ethnic heterogeneity, population density, family disruption, youth, and vacancy. The researchers dealing with spatial aspects of crime claim that census block groups as units of analysis might give better results than census tracts since they are more likely to give finer spatial definition (Harries, 1999). He adds that recent social ecologists have successfully adopted the census block groups to operationalize neighborhoods. In fact, proxy preference for the neighborhoods heavily depends on the size of the city in which a research is conducted. This study, therefore, determines Census block groups as neighborhood proxy since they better fit with the arbitrary boundaries of actual neighborhoods in the City of Richmond. Also, they are the smallest Census geography that provides feasible enough neighborhood characteristics for the purpose of this study.

Of the definitions, neighborhoods should be considered as natural areas bringing local communities together (Sampson, et al., 2002: 445). In fact, certain businesses for land uses and individuals looking for affordable houses might primarily shape the neighborhoods in the urban setting. Therefore, Park and Burges (1925) originally illustrate the neighborhoods as spatially defined areas characterized by ecological, cultural, and sometimes political influences. Further, some communities pose unique identity, and accommodate specific residential groupings (Sampson, et al., 2002). Therefore, neighborhoods should be anticipated as various projections of larger communities.

The previous researchers have actually applied all possible census geographies such as census block groups, census tracts, and counties as they deal with spatial aspects of crime. On the other hand, Eck (2005) posits that most studies in the literature define the neighborhoods in terms of Census tracts and Census block groups. With the advantages of Census data such as the correspondence to each other, the present study prefers to utilize Census Geography to illustrate the boundaries of neighborhoods.

Accordingly, this study examines the distribution of homicides at census block groups, as the appropriate proxies of neighborhoods. Further, it visualizes hotspots of homicide incidents regardless of any boundary in terms of incident locations. Then, this study realizes each hotspot locations fallen into each neighborhoods, observes their movements, identifies sub-selected neighborhoods experiencing homicide hotspot(s), and attempts to explain homicide variation attributable to the changing degree of neighborhood social disorganization over the years.

Population

This study does not require any sampling procedure. It focuses on the City of Richmond as a case study, and attempts to achieve its feasible research objectives. Then, all neighborhoods in terms of census block groups become the target population for this study in the City of Richmond. Since essential data (Census geography, Census data, and crime data) for the entire population are feasibly available as either online or archival information, the sampling is not necessary for the purpose of study. Another advantage of using population would be that studying population does not require rejecting null hypotheses at certain significance levels. That is, the findings would be able to directly reflect the social reality. Although this study still checks the significance level of findings, it does not very much rely upon such confidence levels. Rather, it focuses on how much each explanatory predictor (social disorganization indicator) contributes to explore the change in dependent variables. Also, in which direction (positive or negative) to what extent each variable predicts the variation within the DV would be the primary concern of this study. In this line of reasoning, this study works with all Census block groups (N = 163) as a target population. Further, it works on homicide, as a neighborhood crime, within the same neighborhood geography over the years.

Measurement of Variables

This study classifies the variables in terms of dependent variable, exogenous variables, and control variables. Neighborhood homicides might be explained by various forms of social disorganization characteristics as frequently used in the previous literature. This section covers all conceptual and operational definitions for each variable. In fact, conceptualization and operationalization together result in appropriate measurement (Moriarty, 1999). Since this study deals with a neighborhood level approach to the homicide, the variables are operationalized with aggregate level information obtained from the Census and other secondary data sources.

Here are the mathematically representations (another form of conceptual model) of statistical models that include all variables as follows:

$$Neighborhood\_Homicide_T = f(R, H, F, L, U, Y, V) \qquad \text{Equation 3.1}$$

$$\Delta Nhood\_Homicide\_Rate_{(T+1)-T} = f(\Delta R, \Delta H, \Delta F, \Delta L, \Delta U, \Delta Y, \Delta V) \qquad \text{Equation 3.2}$$

T (year)	: 1990, 1991… 1999.
R	: Residential Mobility
H	: Racial/ethnic Heterogeneity
F	: Family Disruption
L	: Low Socio-Economic Status
U	: Urbanization (population density)
Y	: Youth
V	: Vacancy
Nhood_Homicide_Rate	: Number of homicides per 1000 persons in neighborhoods.
Δ	: Change in the values from T to T+1 year.

In the equation 3.1, neighborhood homicide might be either in the dummy form or rate form to operationalize the dependent variable. However, for homicide analyses by equation 3.1, this study uses dummy form (1 or 0) in the multivariate statistical models. It ultimately uses average form of the neighborhood homicide rates over the 10 years so as to construct one more statistical model in the sub-selected neighborhoods out of all (N =163, Census Block Groups). The equation 3.2, on the other hand, shows difference (change) models including both neighborhood homicide and social disorganization.

Dependent variables (Ratio level):

This study employs the various forms of a neighborhood homicide as dependent variables. In fact, it primarily computes three different dependent variables (DV) such as dummy form of homicide (Equation 3.1), homicide rate differences (Equation 3.2), and average homicide rates (Equation 3.1) over the 10 years. The present study, therefore, constructs a series of specific models-fit for only homicide distribution as a neighborhood crime.

Accordingly, the present study attempts to expand the works of Sampson and his colleagues by testing their Social Disorganization Theory for only homicide as a neighborhood crime in the City of Richmond. Table 3.1 lists all the variables in this study while Table 3.2 presents all exogenous variables with their operationalized versions.

Table 3.1: List of Variables Examined in the Present Study

Dependent Variables	***Exogenous Variables***	*Control Variables*
Neighborhood homicide (1 or 0) Neighborhood homicide rate Neighborhood homicide change	Residential Mobility Ethnic/racial Heterogeneity Family Disruption Low Socioeconomic Status Urbanization (population density) Youth ($12 \leq Age \leq 24$) Vacancy	Dummy for Project Exile Dummy for Blitz to Bloom

Table 3.2 is constructed in specific order, indicating the process of social disorganization that Sampson and Groves (1989) describe in their landmark studies. That is, a breakdown in communities firstly starts because of high residential mobility, ethnic/racial heterogeneity, and family disruption. Then, poverty and urbanization might amplify the disorganization process to some degree. The following sections will argue, in the same order, how neighborhood homicide variation is associated with these exogenous variables that are more likely to confound the social cohesiveness within the neighborhoods.

Table 3.2: Exogenous Variables

Residential Mobility *(Factor Loading)*	***Racial/Ethnic heterogeneity*** *(Interaction Index)*	***Family Disruption***	***Low SES*** *(Factor Loading)*	***Urbanization*** *(Proxy)*	***Youth***	***Vacancy***
Percentage of occupied households living in the same house for less than 5 years	Percentage of white population	Percentage of Female-Headed households with own children	Percentage of population below Poverty line	Population density	12≤Age≤24	Vacant housing units in total housing units
Percentage of Rental occupied housings	Percentage of Black population		Percentage of households having public assistance			
	Percentage of Latino population		Percentage of unemployed individuals in civilian labor force.			
	Percentage API (Asian/Pacific Islanders)					
	Percentage of other pop.					

Exogenous Variables (Independent variables)

Although each exogenous variable might influence the neighborhood homicide, they themselves should not be considered as a direct impact on homicide distribution according the concept of SDT. In fact, some of them might be actually effective on explaining the variation within the neighborhood crime if they are simultaneously processed with other exogenous variables (Cahill, 2004). They might be contingent to each other as they explore the neighborhood crime variation through debilitating the social control within the neighborhoods. Eliott et al., (1996) also addresses various forms of social disorganization so as to realize the contingent measures with some others. That is, different exogenous variables might not invariably influence the crime variation in neighborhood due to the conditional effects of different variables. Each exogenous variable, on the other hand, might be spatially dependent to each other. Meaning that, similar and/or dissimilar neighborhoods with specific exogenous characteristics might be contiguous to each other across the neighborhoods. Consequently, each exogenous variable works as like a control variable while the contribution of each predictor is measured to explain the neighborhood homicide variation (DV).

According to the model of Sampson and Groves (1989), the present study is supposed to deal with five exogenous variables such as Residential Stability, Racial/Ethnic Heterogeneity, Family Disruption, Low SES, and Urbanization. Since the present study works in an absolutely urbanized area in the City of Richmond, it disregards the subject whether urbanized or not. Rather, it utilizes Population Density as the proxy variable for Urbanization. From the view of social disorganization theory, these five exogenous variables all are positively associated with crime, whereas they are negatively associated with collective efficacy (Sampson et al., 1997). In addition what Sampson and Groves performed, this study also includes youth and vacancy as being considered the part of the social disorganization process. Over all, exogenous variables in this study are statistically measured at *ratio level* as Census and neighborhood homicide values (dummy, rate, or rate change) are appropriately prepared for quantitative measurements.

The research further argues the findings of previous studies as realizing both negative and positive impacts of these exogenous variables on various crimes so that it is able to derive its testable hypotheses for the purpose of the study.

Residential Mobility (Ratio level):

Residential mobility is considered as a significant indicator for social disorganization. Residential mobility conceptually refers to movement from one neighborhood to another. It is operationalized by “the percentage of residents who lived in the neighborhood for less than five years (Sun et al., 2004: 5). Moreover, Krivo and Paterson (2004: 9) add two additional proxies to measure the residential mobility: rental occupancy and vacancy rate. They, ultimately, constructed a composite index consisting of the average z-scores as they examined the spatial patterning of crime in terms of race and ethnicity. In fact, residential mobility might be mostly identified in the neighborhoods where renter occupied households are high. In other words, the more renter households in neighborhoods might reveal the higher residential turnover in the neighborhoods. Accordingly, in this study, residential mobility should be quantified in terms of both renter occupied housings and residents who live in the same house for less than five years.

Originally, Shaw and McKay (1942) showed that higher residential mobility lead to a breakdown of social integrity. Kornhauser (1978: 78) further illustrated the same issue about residential mobility, saying that "common interests cannot be discovered or served as the foundation from community organizations when populations change quickly". Further, Sampson et al., (1997) contend that it takes some time to evolve social ties and cohesiveness in the neighborhood. High levels of residential mobility might be a barrier to setup collective efficacy, and eventually lower social control. On the other hand, Roh (2004) addresses the possibility of having less social control despite having more stable community unless individuals interact much to each other within the neighborhoods. Although previous studies have not clearly addressed possible reverse influence of residential mobility, residential mobility might delineate different degree of social disorganization and/or organization. That is, if much more residents with higher socio-economic status move into certain neighborhoods, then residential mobility might make these neighborhoods more socially organized. Even observing less likelihood of this situation, such residential mobility contingent upon the degree of SES might result in less neighborhood crime.

To be consistent with the literature, recent studies suggest that residential mobility is positively associated with crime variation (Cahill, 2004). However, other studies indicate possible conditional effects of residential mobility with poverty as they explore the crime variation at aggregate level. For instance, the association between residential mobility and crime variation is more likely to exist in poor communities than affluent ones (Sullenger, 1950). Meaning that, residential mobility in well-being neighborhoods may not lead to more neighborhood crimes. As another limited weight of residential mobility on social disorganization, residential mobility may not significantly impact on violent crime rates in affluent communities (Roh, 2004: 38). These findings from literature might be a solid foundation to develop a specific hypothesis for the association between neighborhood residential mobility and homicide.

Some studies, on the other hand, prefer to employ residential stability by accounting for the percentage of owner occupied population, and percent occupied households for five years or more in the same neighborhood. Accordingly, residential stability or residential mobility might serve for the same purpose. Then, residential stability can be interpreted as lower residential turnover in the neighborhoods. Sampson et al., (1997: 919) also address residential stability to promote collective efficacy in neighborhoods. Since it takes long time to form close social ties, higher residential turnover might significantly attenuate the level of informal social controls over collective life. The higher residential mobility might lead more social disorganization in the neighborhoods. Then, the neighborhoods exposing higher turnover are more likely to face higher homicide rates in the conceptual model of the present study. And, the degree of change in neighborhood residential mobility might lead to certain degree of change in neighborhood homicide.

Ethnic/racial heterogeneity (Ratio level):

Heterogeneity conceptually refers to diversity in cultural values and norms of various ethnic or racial groups in the neighborhoods (Cahill, 2004: 26). Various norms and values might impede the social consensus since it might negatively influence the communication among the community (Elliott et al., 1996). Therefore, racially and/or ethnically diverse communities are less likely to develop informal social control in the neighborhoods. Such disadvantage might lead to a breakdown in the social cohesiveness. Roh (2004) reviews numerous papers on the heterogeneity, and states that the more heterogeneous neighborhoods might have higher crime rates (Osgood & Chambers, 2000; Warner & Pierce, 1993; Sampson & Groves, 1989; Smith & Jarjoura, 1988). These studies also address that the possible association between heterogeneity and crime may vary depending on the type of crime. For instance, previous studies are more likely to find an impact of heterogeneity on burglary rates (Warner and Pierce, 1993). Further, the impact of heterogeneity on burglary rates is contingent upon the poverty level in their studies. They identified a positive association when poverty is low, but the association was negative when poverty is high.

Ethnic or racial heterogeneity is operationalized identically to what Sampson and Groves (1989: 784) used. They utilized Blau's (1977: 78) interaction index for various groupings. Therefore an index variable for racial/ethnic heterogeneity might be easily constructed by calculating an interaction index among various categories of race and/or ethnicity. Generally speaking, race and/or ethnicity are divided into five different groups such as non-Hispanic whites, Black, Latino, API (Asian/Pacific Islanders), and other. An interaction index is employed as the primary measure of diversity among the population. It is defined as "the degree of potential contact or possibility of interaction" between two or more subject groups (Massey and Denton, 1988: 287). The higher interaction index means the higher diversity within the neighborhood. It is calculated as:

$$S = 1 - \sum_{k=1}^{n} (P_k / P)^2 \qquad 0 \leq S \leq 1$$

n : Numbers of geographic units such as census block groups and census tracts.

P_k : Population of a group in the k^{th} geographic unit

P : Total population within the geographic unit

S : Interaction index value

Alternatively, entropy index might be considered another measurement to calculate variation, dispersion or diversity (Turner et al., 2001). It measures the degree to which racial/ethnic groups are heterogeneously distributed within a neighborhood.

"H" Entropy (or Diversity) Index;

$$H = - \sum_{k=1}^{n} [(P_k / P) * \ln (P_k / P)]$$

$$H = H / \ln(n) \quad \text{(Normalized)}$$

n : Total number of subgroups present in the population

ln : Natural logarithm

$\mathbf{P_k}$: Population of the k^{th} subgroup

P : Total population of all subgroups included in the index

H : Entropy index value

A value of 0 indicates homogeneity, wherein all racial and ethnic groups are of one single type; a value of 1 means the highest heterogeneity, wherein area is evenly distributed among all racial/ethnic categories.

This study prefers to utilize Blau's interaction index as keeping this study consistent with what Sampson and Grove (1989) used in their landmark studies. Another reason to select the interaction index for measuring the heterogeneity is because of its simpler calculations and interpretations. For the sake of simplicity and consistency with previous studies, this study feasibly determines for interaction index as it calculates the race/ethnic heterogeneity.

Family disruption (Ratio level):

Family disruption is another structural neighborhood characteristic leading to higher social disorganization, and weaker social control in the community. Conceptually, family disruption refers to instability of the family. Divorce, separation, and female headed households might all indicate such instability (Cohen and Felson, 1979). Fortunately, macro-social measurement level (like neighborhoods) allows for determining the family disruption and contributing to the neighborhood crime changes over time. However, Cahill (2004:29) specifically posits that family disruption does not contribute to the explanation of the variation within crime or delinquency at the individual level. But, the present study does not explore the crime variation at an individual level.

From the perspective of SDT, Sampson and his colleagues' studies (1986, 1997, and 2003) illustrate the role of family disruption as a significant factor which is likely to attenuate social control in the neighborhood. In specific, Sampson (1987:353) conceptually pointed out that family disruption might tend to weaken social networks through "a weakening of formal and voluntary organizations, many of which play crucial roles in linking local youths to wider social institutions and in fostering desired principles and values." In other words, unsupervised youths with the lack of guardianship (like family) are less likely to form healthy friendship networks in the neighborhood (Cahill, 2004; Sampson, 1997; Sampson and Groves, 1989). Cohen and Felson (1979) also contend that married parents are more likely to supervise and/or protect their children. Then, collective family control might better enhance collective efficacy in the neighborhoods (Sampson and Groves, 1989: 781). Ultimately, if the collective efficacy is improved by family supervision, the studies might realize some positive influence on decreasing neighborhood crime.

From the literature, family disruption has generally been operationalized by similar proxies (percentage of divorce, separated, or female headed households within neighborhoods). For instance, in their landmark study, Sampson and Groves (1989: 785) operationalized family disruption as the sum of z scores of the certain characteristics of family types such as the separated, divorced, and/or the single families with children. Sun and his colleagues (2004), on the other hand, have measured the family disruption by just calculating the percentage of divorced and separated families in the neighborhoods. Likewise, Lowenkamp et al. (2003) operationalized family disruption as identical to

Sampson and Groves (1989: 785). Cohen, Gorr, and Olligschlaeger (1993) further explored the drug hot spots in relation to weak family ties as operationalized by female-headed households only. For the sake of simplicity, the present study prefers to operationalize family disruption by including only one type of family such as female-headed households with their own children as clearly recognized in the Census data.

In considering the unique characteristics of these types of families, most single parent households might have less economic power than dual-parents (Rice and Smith, 2002). For this reason, family disruption should be controlled by socioeconomic status as measuring its actual contribution on predicting the variation within neighborhood crime. Accordingly, family disruption is more likely to be positively associated with neighborhood homicide variation as it is statistically controlled by SES.

Socioeconomic Status (SES) (Ratio level):

SES has been employed by most social ecologists since the first study on Social Disorganization Theory. Conceptually, low economic conditions refer to scarcity of money and resources (Sampson and Groves, 1989: 780). Most studies have, therefore, considered poverty as a low SES indicator in the Social Disorganization Theory literature. In fact, poverty is likely to be a strong structural characteristic exaggerating social disorganization. In other words, higher poverty levels might not allow the residents to obtain basic necessities, and to maintain their community in a better way (Cahill, 2004: 24). Consequently, absence of resources that are necessary to enhance their community might also weaken the social control and networks in the neighborhoods. Cahill (2004) further posits that neighborhood poverty is likely to bring about isolating some communities from the mainstream of the city.

Although their approaches are different on control variables and operationalization, many scholars have studied the association between poverty and high crime in the city (Roh, 2004). They have mostly found positive relations between poverty and high crime rates by holding other structural factors of social disorganization constant. For instance, Lander (1954) proved such a positive association between poverty and crime variation in certain areas where residential mobility is highly observed. Accordingly, poverty, even if a strong indicator of social disorganization, may predict the variation within the crimes provided that one could account for other related indicators, such as home ownership, median income, median house value, and education (Shaw and McKay, 1942). In the present study, SES is primarily controlled by residential mobility.

On the other hand, poverty might be categorized in regarding to absolute and relative poverty (Paulsen and Robinson, 2004: 27). Absolute poverty refers to various poverty levels in a region, while relative poverty means the distinction between poverty and wealthy neighborhoods across the city. Roh (2004) reviews the following absolute proxy values of SES from the literature: Median family income, percentage of households below a poverty line, unemployment rates, and proportion of overcrowded households. Back to importance of SES in social disorganization concept, individual victimization rates are positively associated with the proportion of the households below poverty line (Sampson and Catellano, 1982). In their study, the number of households below poverty line must have been considered as absolute poverty.

Relative poverty, defined as the dispersion of income over certain region, is considered more important than absolute poverty level (Roh, 2004; Blau and Blau, 1982). In fact, income inequality is mostly operationalized by the Gini index of income dispersion as it is employed for relative poverty measurements (Paulsen and Robinson, 2004). However, in Messner’s study (1982), the contribution of relative poverty on explaining the homicide rates ceased as demographic indicators were controlled. Relative poverty approach might be better implied at city level or larger scales so as to calculate the Gini index of income. Despite such statistical results, lower homicide rates have been observed within the specific areas where the households are mostly under the poverty line (Roh, 2004).

Accordingly, the present study operationalize low SES in terms of percentage population below poverty line, percentage of households having public assistance, and percentage of unemployed individuals in civilian labor force. In fact, factor analysis is utilized to establish such a composite variable for SES. Factor analysis basically captures the commonalities of these three Census variables, and lets the research construct a representative principle component instead of using them separately in the models.

Urbanization (Population density) (Ratio level):

This study utilizes population density as a proxy of urbanization since the City of Richmond is already considered fully urbanized. Rather than dropping urbanization variable from the conceptual model, it prefers to keep the population density as a proxy of urbanization to explain the variation within neighborhood homicide. Conceptually, population density is defined as “a heavy concentration of people residing in an area” (Paulsen and Robinson, 2004: 62). It might be operationalized as the ratio of number of people living in a neighborhood to its area (# of people / area of neighborhood). Population density has also been measured as the number of persons per household in some studies. In other words, the more people living within a unit area address the higher population density in the neighborhoods. In fact, this is important indicator to investigate the socially disorganized neighborhoods since higher population density might be an important source to exaggerate the level of social disorganization. Some census block groups, as the proxy of neighborhoods, may not have any population since their land use configuration might only consist of parks and public open space. Consequently, this study expects higher neighborhood homicides in denser neighborhoods across the city.

However, Cahill (2004:31) challenges the role of population density as the proxy variable for urbanization. Some studies have differently interpreted the possible impact of population density on the crime variation. In fact, Stark (1996) recognizes the significant association between the greater population density and the higher possibility of forming unsupervised youth groups since young people are more likely to spend time outside of their residences in such neighborhoods. In this line of reasoning, such denser neighborhoods might be more attractive to increase neighborhood level homicides. Cahill (2004:32), on the other hand, argues that greater densities might enhance the levels of informal social control. Meaning that, more residents in neighborhoods might keep their eyes on their territories. In spite of such vague conceptualization, it can be reflected that higher population density might attenuate the social ties to setup, and, therefore, might surge opportunities of crime incidents in the neighborhoods.

Youth:

Sampson et al., (1997) and previous studies have utilized youth as an indicator for socially disadvantaged neighborhoods. As one considers the collective efficacy to better supervise children and young population, youth variable might play significant role to delineate the level of social disorganization in the neighborhoods. Spatial pattern of young population within contiguous neighborhoods across the city might further increase the role of young age composition. That is, it might be more difficult to supervise such higher percentage of young population in the contiguous neighborhoods. Also, young population in higher heterogeneous neighborhoods might become more important predictor to explain neighborhood crime variation. Young people from different race/ethnic background are less likely to try to understand each other. Focus to homicide, Land et al., (1990) specifically discusses the association between homicide rates and the concentrated teenage/young adults. In fact, they posit that youth population is positively related to the variation in homicide rates. According to Land et al., therefore, teenagers and young people are lore likely to commit a crime than other individuals at other ages can. Accordingly, the present study expects to realize higher neighborhood homicide in socially disorganized neighborhoods having more young population.

In terms of the operationalization, youth might be calculated in two different classifications such as juveniles (age <18) and older youth (ages 18 to 24) (Butts, 2000:2). Some studies, such as Sampson et al., (1997), prefer to calculate the age lower than 18 as the young population. Nevertheless, it may not be sensible to include the persons less than 12 ages as young population. They are just kids at lower than 12 ages. Again, some research defines the youth as persons between 15 and 25 ages, whereas some others define between 12 and 25 ages for the youth population (Wikipedia, 2007). Clearly, definitions about youth vary too much. The present study, however, wants to completely cover young population by including both juveniles and older youth. And, it comes with the ages between $12 \leq$ persons ≤ 24 as this definition relies upon the age categories of Census data and commonly preferred range in the literature.

Vacancy:

Vacant housings are considered public signs of disorder in the literature (Sampson et al., 1997). Some studies also utilize higher vacancy rates as indicator of disadvantaged neighborhood. Especially, the researches dealing with neighborhood revitalization and urban renewal have utilized vacant housing rates to estimate the association between environmental conditions and crime distribution. Further, literature address that vacant housings are more likely to be associated with violent crime. Schumacher and Michael (1999) developed some models to detect crime displacement thanks to the redevelopment investments and procedures in the city of Baltimore. They consider such enhancing procedures on vacant/abandoned buildings as pushing factors leading to change crime patterns over time. Accordingly, the city officials would like to invest some dollars to decrease the vacancy rate, and increase the homeownership as they aim to enhance the collective efficacy in community. From the perspective of social disorganization, higher vacancy rate might indicate higher disorganized neighborhoods in some degree.

Control variables:

According to Nachmias and Nachmias (2000), control variables should be included for a solid conceptual model. Studies, therefore should acknowledge other possible variability associated with neighborhood homicide variation. Control variables are basically utilized to assure the relationships amongst the variables to test hypotheses, and to result in appropriate covariates in the statistical model. Some exogenous variables might also be utilized as control variables while they work as social disorganization indicators. In addition to these social disorganization indicators as control variables, this study should also consider crime policy programs as control variables.

This study, therefore, realizes two main policy programs in the period of working time such as Project Exile and Blitz to Bloom. As it investigates the association between neighborhood social disorganization and neighborhood homicide over the years, it acknowledges these policy programs, and includes them as control variables in the models. They are added as dummy variables for the years whether these programs are implemented or not. For instance, Blitz to Bloom is declared as dummy variables for some neighborhoods treated by this program or not over the years. Accordingly, this study reliably explores the contribution of each social disorganization indicator on explaining the variation of neighborhood homicide over time. In fact, adding them as control variables would be able to avoid from possible superior influences of structural covariates in the model.

Hypotheses

The hypotheses below are tested for the neighborhood homicide. In fact, different versions of homicide values (such as likelihood, differences, and average rate values) are utilized as the dependent variables (DV). As seven exogenous variables of social disorganization; residential mobility, race/ethnic heterogeneity, family disruption, low SES, population density, youth, and vacancy are treated as independent variables (IV). As this study tests each hypothesis constructed for each social disorganization variable, dummy variables for Project Exile and Blitz to Bloom serve as control variables in the models.

The present study focuses on eight (8) hypotheses so as to answer its research questions. In the first seven (7) hypotheses, they are separately tested for the neighborhood homicide in each time step. Once testing these hypotheses, the present study compares and interprets the coefficients with respect to the previous findings on Social Disorganization Theory, and possible outcomes of various policy considerations (Project exile and Blitz to Bloom) during the working period of this research. In the first seven hypotheses, dependent variable are dummy variable (1: Yes Homicide; 0; No Homicide), rate, and average rate for neighborhood homicide. In eighth (H_8) hypothesis, this research, on the other hand, uses neighborhood homicide rate change with the categories (e.g., increase, decrease, and no change in homicide) as dependent variables. The DV for the last hypothesis, therefore, will have three categories. Independent variables, on the other hand, include the changes of social disorganization indicators (at ratio level) in the neighborhoods from 1990 to 1999. The Census data provide these variables with comprehensive information at Census block group level. Incident level crime data (individual homicide events with dates, and addresses) are obtained from the City of Richmond Police Department. Once homicide incidents are aggregated to neighborhoods, this study computes their rate and difference values as well as dummy values across the neighborhoods for each year.

Accordingly, the probability of having neighborhood homicide (e.g., dummy form of homicide), the probability of having neighborhood homicide change (e.g., three categories of homicide change), and changing characteristics of neighborhoods all should be examined together to better understand the context of the neighborhood homicide in the light of Social Disorganization Theory. The relations amongst them might provide the social policy makers and police managers with a comprehensive approach in exploring the context of neighborhood homicide and in improving their decision making process.

Although this study constructs the following alternative hypotheses for the purpose of the study, it is not supposed to reject their null hypotheses at certain significance level since this study, as mentioned before, use entire target population, and the possible findings directly reflect the actuality in the City of Richmond. The only important point is whether the contributions of social disorganization variables are consistent with SDT or not with respect to their magnitudes and directions. Here are the alternative hypotheses to test and accomplish the purpose of the study:

- H_1: As “residential mobility” increases so does the neighborhood homicide
- H_2: As “race/ethnic heterogeneity” increases so does neighborhood homicide
- H_3: As “family disruption” increases so does neighborhood homicide
- H_4: As “socio-economic status” decreases so does neighborhood homicide
- H_5: As “population density” increases so does neighborhood homicide
- H_6: As “youth population rate” increases so does neighborhood homicide
- H_7: As “vacancy rate” increases so does neighborhood homicide
- H_8: Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time

Note that, the main hypothesis of this research is “*Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time.*”

H_1: As “residential mobility” increases so does the neighborhood homicide

This is one of the most important hypotheses in testing social disorganization. That is, social ecologists show that higher mobility might lead to breakdowns in informal social control (Shaw and McKay, 1942; Kornhauser, 1978, Samson and Grove, 1989). New residents coming from different cultural and social background might not adopt themselves in a short time. Residential mobility should be considered a major obstacle to establish social networks. Residential mobility might, therefore, attenuate the informal social control in the neighborhoods. As a result, less informal social control might be positively related to neighborhood crimes. Residential mobility will be measured by percent occupied households living in the same house for less than 5 years and renter occupied housings together. A factor loading of these variables will be utilized to obtain values for the residential mobility.

Accordingly, residential mobility is independent variable, whereas neighborhood homicide (dummy, rate, or average rate) works as dependent variable in this hypothesis. All other variables in the conceptual model work as control variables such as race/ethnic heterogeneity, family disruption, low SES, population density, youth, and vacancy as well as dummy variables for the policy program. Dummy variables for the policy programs also work as control variables in testing this hypothesis. The present study expects that community level residential mobility might be positively associated with the neighborhood homicide variation.

Binary Logistics Regression analysis is the primary statistical method to determine whether the residential mobility influences the odds of neighborhood homicide as other variables are controlled in the model. After making the sub-selection of the neighborhoods that have homicide hotspot(s) over the ten years, this hypothesis is also tested by multiple regressions model so as to investigate whether the average residential mobility explains the variation within the average neighborhood homicide rate over ten years, and still supports the theory in these specific neighborhoods. Accordingly, this study will be able to determine if residential mobility significantly influences the neighborhood homicide rate in the most problematic neighborhoods with respect to having homicide incidents hotspot(s).

H_2: As "race/ethnic heterogeneity" increases so does neighborhood homicide

Race/ethnic heterogeneity is considered another barrier to establish consensus on common values from the social ecologist's point of view. While individual groups might better reach a consensus on commonalities in their territories, more heterogeneous communities might attenuate the degree of such consensus. Accordingly, higher racial/ethnic heterogeneity with less informal social control is likely to increase neighborhood homicide.

Race/ethnicity heterogeneity will be operationalized by the interaction index as preferably used by Sampson and Groves (1989) in their studies. Neighborhood homicide (dummy, rate, or average rate) is DV, whereas race/ethnic heterogeneity becomes IV in testing this hypothesis when other structural variables are controlled in the model such as residential mobility, family disruption, low SES, population density, youth, and vacancy. Dummy variables for the policy programs also work as control variables in testing this hypothesis.

Binary Logistics Regression analysis is the primary statistical method to determine whether the race/ethnicity heterogeneity supports the Social Disorganization Theory or not as others are controlled in the model. After making the sub-selection of the neighborhoods that have homicide hotspot(s) over ten years, this hypothesis is also tested by multiple regressions model so as to investigate whether the average race/ethnic heterogeneity explains the variation within the average neighborhood homicide rate over ten years, and still supports the theory in these specific neighborhoods. Accordingly, this study will be able to determine if race/ethnic heterogeneity significantly influences the homicide rate in the most problematic neighborhoods with respect to having homicide incidents hotspot(s).

H_3: As "family disruption" increases so does neighborhood homicide

Social ecologists have mostly argued that family disruption might attenuate the degree of informal social controls in the communities. Sampson and Grove (1989) contend that two married households might not only better supervise their children, but also more carefully observe general activities (especially strange ones) in their territories. If neighborhoods are more likely to have community-level married families with their children, family network become more effective mechanism to protect their communities. Interestingly, Samson and Grove (1989) argue that higher community-level family disruption might directly lead to higher crime rates by different race/ethnic groups.

Family disruption will be operationalized by percentage of female-headed households with children over the total number of families according to the Census data. Neighborhood homicide (dummy, rate, or average rate) is dependent variable, whereas family disruption becomes independent variable in this hypothesis. All other variables in the conceptual model work as control variables such as residential mobility, Race/ethnic heterogeneity, low SES, population density, youth, and vacancy. Again, dummy variables for the policy programs also work as control variables in testing this hypothesis.

Binary Logistics Regression analysis is the primary statistical method to determine whether the family disruption supports the Social Disorganization Theory or not as others are controlled in the model. After making the sub-selection of the neighborhoods that have homicide hotspot(s) over the ten years, this hypothesis is also tested by multiple regressions model so as to investigate whether the average percentage of family disruption explains the variation within the average neighborhood homicide rate over ten years, and still supports the theory in these specific neighborhoods. Accordingly, this study will be able to determine if family disruption significantly influences the homicide rate in the most problematic neighborhoods with respect to having homicide incidents hotspot(s).

H_4: As "socio-economic status" decreases so does neighborhood homicide

Social ecologists agree that lower income resources might lessen the degree of social informal control and networks. Neighborhoods having higher level of poverty might not allow maintaining the community with strong ties due to the lack of monetary capacity to meet very basic essentials. However, SES itself cannot explain the homicide variation without accounting other important social disorganization predictors in the neighborhoods. Poor individuals might also be willing to keep their environment safer. All other structural characteristics together with higher poverty level might better explain the variation in neighborhood crime.

In this hypothesis, SES is measured by the factor loading (Principle component) accounts for the commonalities of the percent of population under the poverty line, percentage of households having public assistance, and percentage of unemployed individuals in civilian labor force. In fact, each of them is considered suitable proxy for low SES. However, this study might face some inconsistent errors over years if they are individually utilized in the statistical models. The present study, therefore, utilizes factor loadings to establish the low SES as one unique variable in the model. The DV becomes neighborhood homicide in different formats such as dummy, rate, or average rate. Low SES is considered as IV in testing the hypothesis when other variables are controlled in the model such as residential mobility, race/ethnic heterogeneity, family disruption, population density, youth, and vacancy. Dummy variables for the policy programs from 1990 to 1999 also work as control variables in testing this hypothesis. The impact of low SES on explaining the neighborhood crime variation might be contingent upon with these control variables as Cahill (2004: 26) investigates them for urban crime geography. SES has already been utilized by previous studies dealing with possible association between neighborhood characteristics and various crime distributions.

Binary Logistics Regression analysis is the primary statistical method to determine whether the low SES supports the Social Disorganization Theory or not as others are controlled in the model. After making the sub-selection of the neighborhoods that have homicide hotspot(s) over the ten years, this hypothesis is also tested by multiple regressions model so as to investigate whether the average low SES explains the variation within the average homicide rate over ten years, and still supports the theory in these specific neighborhoods. Accordingly, this study will be able to determine if low SES significantly influences the homicide rate in the most problematic neighborhoods with respect to having homicide incidents hotspot(s).

H_5: As "population density" increases so does neighborhood homicide

Population density is included as a proxy for the urbanization from the perspective SDT. This study expects to realize its attenuating impact on informal social control. Therefore, it expects higher homicides in the neighborhoods with higher population density. It might be more difficult to supervise youth population in the neighborhoods with higher population density. However, population density and vacancy rate should be considered together while examining the homicide in the neighborhoods. In fact, the more vacant housings might indicate the less population density. Such vacant areas and less populated neighborhoods might, therefore, provide criminals with more opportunities to commit homicides. All other variables in the conceptual model work as control variables such as residential mobility, Race/ethnic heterogeneity, family disruption, low SES, youth, and vacancy. Dummy variables for the policy programs from 1990 to 1999 are also initiated as control variables in this hypothesis. Population density is operationalized as the ratio of number of people living in a neighborhood to its area (# of people / area of neighborhood).

Binary Logistics Regression analysis is the primary statistical method to determine whether the population density supports the Social Disorganization

Theory or not as others are controlled in the model. After making the sub-selection of the neighborhoods that have homicide hotspot(s) over the ten years, this hypothesis is also tested by multiple regressions model so as to investigate whether the average population density explains the variation within the average homicide rate over ten years, and still supports the theory in these specific neighborhoods. Accordingly, this study will be able to determine if population density significantly influences the homicide rate in the most problematic neighborhoods with respect to having homicide incidents hotspot(s).

H_6: As "youth population rate" increases so does neighborhood homicide

This hypothesis is additionally included to expand the model Sampson and Groves (1989) constructed. This hypothesis expects that the neighborhoods with higher number of young population are more likely to experience neighborhood homicide. However, having more young population does not recognize whole social disorganization process. More realistically, degree of young population might be contingent upon the level of SES and family disruption in the neighborhoods. In the neighborhoods with higher residential mobility might be more concerned about having more young population. These social disorganization indicators together are more likely to attenuate the degree of informal social control in the neighborhoods. Young population might be positively associated with the degree of neighborhood crime.

The young population includes the persons between $12 \leq age \leq 24$ according to the Census data. And, it is operationalized as the percentage of youth population over total population in the neighborhoods.

Binary Logistics Regression analysis is the primary statistical method to determine whether the young population supports the Social Disorganization Theory or not as others are controlled in the model. After making the sub-selection of the neighborhoods that have homicide incidents hotspot(s) over the ten years, this hypothesis is also tested by multiple regressions model so as to investigate whether the average percentage of youth population explains the variation within the average homicide rate over ten years, and still supports the theory in these specific neighborhoods. Accordingly, this study will be able to determine if young population significantly influences the homicide rate in the most problematic neighborhoods with respect to having homicide incidents hotspot(s).

H_7: As "vacancy rate" increases so does neighborhood homicide

The vacancy rate is also included to the original model of Sampson and Groves (1989). As mentioned before, SDT considers vacant buildings as the source of social disorganization in the neighborhoods. The more vacancy rates the more socially disadvantaged neighborhoods. Then, these neighborhoods might experience more neighborhood homicide and other violent neighborhood crimes. As Schumacher and Michael (1999) posit that such unique characteristics in the neighborhoods might be "pulling factors" for the crimes. Vacancy rate is operationalized as the percentage of vacant/abandoned buildings over the total number of housings in the neighborhoods.

Binary Logistics Regression analysis is the primary statistical method to determine whether the vacancy rate supports the Social Disorganization Theory or not as others are controlled in the model. After making the sub-selection of the neighborhoods that have homicide incidents hotspot(s) over the ten years, this hypothesis is also tested by multiple regressions model so as to investigate whether the average percentage of vacant housings explains the variation within the average homicide rate over ten years, and still supports the theory in these specific neighborhoods. Accordingly, this study will be able to determine if vacancy significantly influences the homicide rate in the most problematic neighborhoods with respect to having homicide hotspot(s). Note that, population density and vacancy should be interpreted together in the models.

H_8: Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time

This is the main hypothesis of entire study. Neighborhood homicide rate might have positively or negatively changed due to the change (decrease or increase) in neighborhood composition over time. That is, change in the neighborhood social disorganization across the city is likely to explain the neighborhood homicide change from the perspective of Social Disorganization Theory. In fact, social tension might increase due to the increase in neighborhood social disorganization. Notably, community level characteristics of neighborhoods are more likely to vary as a result of various social policy programs, residential mobility, and other governmental supports to certain communities over time. If neighborhoods with different structural characteristics explain different crime variation at different time intervals, then the community/neighborhood change are also supposed to be the choice to explain the change in neighborhood homicide rate over time. In fact, neighborhood crime distribution might change due to the way if different residences with different characteristics (e.g., more/less affluent people) move in and out across the neighborhoods, if percentage of young population changes due to the residential movements, and if percentage of vacant buildings changes, public signs of disorder, in the neighborhoods. Accordingly, various neighborhoods having exposed various contextual changes might also experience neighborhood homicide change in their territories over time.

Neighborhood homicide rate change is basically calculated by the difference between homicide rate in one year and the subsequent year (e.g. between 1990 and 1999). Then, these changes are recoded with respect to "increase", "decrease", and "no change". Therefore, the DV has three different categories to construct the various difference models for various years' ranges from 1990 to 1999. The changes in the neighborhood social disorganization are utilized as independent variables (ratio level), whereas neighborhood homicide rate change (with three different categories for the homicide) becomes dependent variable to test this hypothesis. This hypothesis is tested for each structural change variable (IVs: change in residential mobility, change in race/ethnic heterogeneity, change in family disruption, change in the low SES, change in population density, change in youth rate, and change in vacancy rate). For instance, residential mobility *increase* is likely to influence the odds of the neighborhood homicide *increase* (DV) as controlling other change variables in the model. Changes in dummy variables for the policy programs are also be included as control variables in these difference models.

Multinomial Logistics Regression analysis is the primary statistical method to construct the difference models for the homicide and to investigate whether each hypothesis for each change variables is supported or not as the other change variables are controlled in the model.

Analytical Techniques

The present study analytically approaches its research questions and hypotheses in five phases: First, data preparation and descriptive statistics will be performed before any in-depth analyses. Factor analysis is specifically used to establish composite variables including multiple variables for the residential mobility factor and the low SES factor. Second, binary logistic regression analysis is performed for homicides across the neighborhoods since they are determined as rare events. This study recodes the homicide incidents whether the neighborhoods experience any homicide incident(s) or not. This study, therefore, will be able to test the essential hypotheses (first seven hypotheses) for the Social Disorganization Theory. Third, Multinomial Logistics Regression analysis is used to construct various difference models to test the main hypothesis (H_8). Fourth, this study investigates the distribution of homicide incidents across the geography regardless of any neighborhood boundaries. It descriptively illustrates the homicide hotspots overlying across the neighborhoods. And, it computes the Moran's I statistics whether homicide rates are spatially autocorrelated across the neighborhoods in each year. Then, it determines the neighborhoods having homicide incidents hotspot(s), and shows them together in a thematic map by GIS. It allows the research to narrow down the most problematic neighborhoods (with respect to having homicide hotspot[s]) in the City of Richmond over the entire years. Last, this study constructs a multiple regression (MR) model for these neighborhoods only as it aims to identify the most important structural covariates influencing the variation within homicide rate across these neighborhoods. In this MR model, this study computes the average values of both dependent variable (homicide rates) and independent variables (7 social disorganization variables). It, therefore, explores variation within the average homicide rate by average values of neighborhood disorganization variables over the entire years. The possible results might help this research target the most problematic neighborhoods with their most important predictors in the City of Richmond. Accordingly, this study will be able to offer efficient and effective policy considerations for the City of Richmond.

Descriptive Statistics

Descriptive statistics will help the research get familiar with the data set in terms of the frequencies, sample size, mean, standard deviation, etc., as well as locating the DV and IVs. This study compares the scores of central tendency and dispersion scores from 1990 to 1999. It, therefore, determines if there is any variation in both neighborhood homicide(s) and structural covariates from 1990 to 1999.

Multivariate Statistics

Factor Analysis

In data process, principal components and factor analysis (as multivariate statistics) might be useful tools to establish more reliable operational variable by reducing the number of potential variables for specific neighborhood social disorganization variables (e.g. residential mobility and low SES). According to Tabachnick and Fidell (2001), *Factor analysis* is used to uncover the latent structure (dimensions) of a set of variables. It reduces attribute space from a larger number of variables to a smaller number of factors. Before running the factor analysis in SPSS, one should meet its all assumptions. The proxy indicators of neighborhood characteristics let the study establish reliable factors. If the study realizes certain factor loadings, then it would be able to address the most appropriate combinations of neighborhood characteristics for low SES (as declared in the conceptual model). In fact, this study expects only one factor loading for the residential mobility since it only loads two observed variables. On the contrary, low SES might generate more than one factor loading since it loads three observed variables. However, this study will only keep the one with eigenvalue ≥ 1 (Tabachnick and Fidell, 2001).

Binomial (Binary) Logistic Regression Analysis

When dummy variable is used as an outcome variable, binary logistic regression allows the researcher predict the likelihood of having homicide or not across the neighborhoods. The predictor variables (independent variables) might be the set of either dichotomous and/or continuous variables (Mertler and Vannatta, 2005). If one independent variable has more than two categories in nature, the researchers need to declare them as dummy variables in logistic regression models. This study, however, has only included continuous level predictors into the model, except Blitz to Bloom as dummy variable. The dependent variable becomes a dichotomous one; meaning that, the neighborhoods experiencing at least one homicide will be "1", whereas the ones having no experience will be "0". Notably, binary logistic regression analysis does not require any rigid assumptions about the distribution of neighborhoods with respect to being normally distributed/ linearly associated, and/or equal variance within the groups "1" and "0".

Multinomial Logistic Regression (MLR) Analysis

Multinomial Logistic Regression is utilized to predict the probability of each class within dependent variable (having 3 or more classes within) in terms of a set of predictors (IVs) (Garson, 2007). IVs might be continuous, discrete, or just mix of them. The IVs, in other words, might be either factors and/or covariates. The ultimate goal, therefore, is to classify the categories of outcome variable based on various types of independent variables. From this perspective, multinomial regression might be considered similar to *binomial logistic regression*, whereas multinomial logistic regression is not just restricted to DVs with only two categories. The basic assumption is that odds ratio of *any two* categories be independent of all categories within DV. Covariates should also be independent to each other in MLR model.

In this study, dependent variable has three different neighborhood homicide change categories such as "decrease", "no change", and "increase" in difference models constructed by MLR. To logically test the main hypothesis (Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time), this study declares the "no change" as a reference category, and interprets "increase" and "decrease" with respect to "no change" category.

Hotspot Analysis, Moran's I Statistics, and Spatial Autocorrelation

Many specialists and researchers have defined hot spots (crime clusters) in different ways. For instance, Harries (1999, p.112) defines the term hot spot as "A condition indicating some form of clustering in spatial distribution." He, however, does not address each cluster as a "hotspot." Adding that, hotspots can be identified by incorporating three different criteria including frequency, geography, and time. Researchers might prefer some or all of these factors to observe any crime hotspot movements. Roh (2004: 48) posits that hotspots are more likely to be identified in the localities where higher crime rates are observed and there is a lower probability to see hotspots in other areas.

Eck (2005) brings a very solid perspective to identify the hotspots in the geographically distributed incidents at various scales, and addresses the common sense on hotspots as "A hotspot is an area that has a greater than average number of criminal or disorder events, or an area where people have a higher than average risk of victimization." The crucial point is to be able to decide specific structural factors that possibly derive the hotspot places as studying from the point level (incident location) to county level (area) (Hirschfield et al. 1997).

The current study posits that spatially integrated methodology might help the researchers to construct the best fitted statistical models to understand the context of homicide occurrences. This is because the variation of crime context might be spatially autocorrelated to manage the spatial variations of crime within other neighborhoods throughout the whole city (Anselin et.al, 2000). Once the present study investigates the possibility of spatial autocorrelation, it attempts to take spatial autocorrelation into account to determine the significance of homicide hotspots across the neighborhoods, and to narrow down the most problematic neighborhoods for the policy consideration.

In other words, crimes in one neighborhood may also be dependent upon the neighborhood crime observed in contiguous census block groups. In geography, everything is more likely to be associated with everything else. Near subjects, however, might be more associated than distant ones. Anselin et al., (2000) also appreciate spatial autocorrelation when the researchers want to investigate the dynamics of crime hotspots through revealing the significant association between crime and location over time.

Spatial autocorrelation in outcome variable (e.g., homicide rates) might become an issue when essential outcome data are aggregated into aerial units such neighborhood, county, city, and state (Morenoff and Sampson, 1997: 42). As Morenoff and Sampson (1997) report in their studies, this study addresses two important points why spatial autocorrelation might be necessary to account for. One is that population change is more likely to be continuous process such that some changes in one neighborhood might also influence one another around. Second point would be various rationalities for housing and lending strategies in the city. Their effects on neighborhood context might be different across space. The models including possible spatial effects with certain variables might, therefore, capture spatial proximity of both neighborhood disorganization and neighborhood homicide change over time as accounting the changes in neighborhoods surrounding one neighborhood.

In fact, spatial weight matrix might be calculated by either distance or contiguity as the researcher defines the distribution of neighborhoods across the urban setting (Anselin, 1988). However, since the census geography has various sizes, the distance criteria might not be an objective criterion as calculating the spatial weight. In this study, therefore, the weights matrix is expressed as first order contiguity, which defines neighbors as having a common border to one another (Sampson and Morenoff, 2004).

This study, however, cannot construct a spatial regression models for the homicide at neighborhood level due to the lack of sufficient variation within homicide rates across the neighborhoods in the City of Richmond. Rather, it benefits from the existing spatial autocorrelation across the neighborhoods with respect to homicide rates in each year. It, therefore, can reasonably select very specific neighborhoods exposing homicide hotspot(s) over the years.

Multiple Regression Analysis

As discussed before, the multiple regressions model is applied for the only neighborhoods experiencing homicide hotspot(s) over ten years. This method may not be used for the entire neighborhoods since the homicide incidents are very rare events across the neighborhoods, and most of the neighborhoods have just “zero” incidents. The outliers and rareness of the homicide incidents across the neighborhoods might be problematic to construct a robust multiple regression model. Instead, this study determines to run multiple regression on the certain neighborhoods having homicide hotspot(s) only, and aims to explore the unique characteristics of these neighborhoods with respect to the average of homicide rate and the average scores of seven neighborhood social disorganization variables over ten years. With averaging, this research aims to take the extrinsic impact of time (years) into consideration. This study will be able to determine the contribution of each predictor on explaining the variation within the average homicide rate as controlling the other average structural covariates in the model.

Multiple regression can establish that a set of independent variables explain some proportion of the variance in a dependent variable at a significant level (significance test of R^2), and can establish the relative predictive importance of the independent variables (comparing beta weights). For the multiple regression analysis, the model is supposed to have a continuous dependent variable, and the various IVs with different measurement levels (usually continuous).

Multiple regression analysis includes the prerequisite assumptions before finalizing the model. One assumption is the absence of outliers among the IVs and on the DV. Another is about the normality, linearity, and homoscedasticity of residuals. One is the independence of errors. Last assumption is that IVs are not supposed to have multicollinearity among them.

According to Tabachnick and Fidell (2001), multiple regression models have the following assumptions:

- The number of cases is supposed to be more than the number of IVs
- Normality, linearity, and homoscdesticity of residuals
- Absence of outliers among the IVs and on the DV.
- Absence of multicollinearity and singularity
- Independence of errors

Before analyzing the average homicide rate with the average values of seven continuous neighborhood social disorganization variables, this study copes with, and has to meet these assumptions in order to reliably interpret the results of multiple regression analysis.

Validity & Reliability Issues

Generally speaking, quantitative methodologists attempt to explore causal/non-causal relationships in the research issue by conceptualization, operationalization, measurement and analyses of information through numerical data explicitly deriving variables (Nachmias and Nachmias, 2000). They utilize statistical instruments to analyze large number of cross-sectional or longitudinal observations with the variables at various measurement levels. Therefore, Quantitative analysis relies on gathering a large number of observations for the purpose of finding correlations between variables (Neuman, 2000).

The findings of various researches might be precisely obtained by a solid research design that acknowledges all the components of reliability and validity (Nachmias and

Nachmias, 2000). Therefore, the present study carefully thinks about both reliability and validity concerns in the following context.

Reliability recognizes the consistency of findings as one repeatedly measures the same expected assessments with no significant change over different measurements. The present study retests the seven primary hypotheses with reliable conceptualization of Social Disorganization Theory in the first phase. In second phase, it attempts to expand the role of social disorganization so as to measure the change in neighborhood homicide rate change. Since the present research tries to confirm the previous findings of Social Disorganization Theory in the City of Richmond, and tries to expand one more step ahead with the second phase as compared to the existing literature, it does meet reliability concerns. Census data and UCR data are commonly used for the purpose of similar studies in the literature. Census, therefore, has provided the researchers with pretty reliable and valid data sources in social science studies. After gathering the data, Census and UCR officials have been cleaning the data to establish standardized dataset for nationwide studies. Accordingly, the present study does not recognize any major threats against the reliability of the study.

Validity, on the other hand, assures about "Am I Measuring what I intend to measure" (Nachmias and Nachmias, 2000:149). The researcher, therefore, should be aware what he/she wants to accomplish from the very beginning to the end of the study. They need to meet the essentials of content validity, empirical validity, and construct validity through the entire research. In terms of *content validity*, the present study utilizes very similar conceptual model as previous SDT studies model, and therefore assures about relevant conceptualization and appropriate operationalization in the light of a comprehensive literature review about Social Disorganization Theory. The present study further uses very clear conceptual definitions for the *construct validity*.

Accordingly, operationalized variables are consistent with the convenient conceptualization. In fact, it uses very similar conceptual definitions for indicators of social disorganization as in previous studies. On the other hand, the present study works for entire population with 163 cases (neighborhoods) and all homicide incidents in the City of Richmond. It also expects to possibly control the extrinsic effects of time by calculating the differences for both crime and neighborhood social disorganization in its empirical analyses. Again, it also aims to have full representative cases (neighborhoods) as it works with entire population in the City of Richmond. Dummy variables for the policy programs might also help the research assure about the over all empirical validity in this study.

Since this study utilizes UCR (Universal Crime Report) type index crimes for its neighborhood crime definition, it works presumably reliable neighborhood crime data for the purpose of the research. In fact, UCR is nationally managed by the FBI, and the Police departments have to follow the same procedures and rules to maintain UCR type crimes in their database. That is, unique analytical methodology of this study might also be applied to other locations in United States. However, the results of the study should be interpreted in terms of both the elements of Social Disorganization Theory and various policy implications in the City of Richmond. As a result, such an approach guided by Social Disorganization Theory provides theoretical, methodological, and policy oriented contributions to the literature around spatially integrated social policy and law enforcement applications.

Limitations of the Study

This study is limited by the constraints of secondary data analysis. In particular, the misspelled addresses of incident locations are considered the primary concern in this study. Nonetheless, the incident locations not located on the map might be manually geocoded within GIS environment until we obtain at least 80% of matching cases.

Since this study cannot access the neighborhood information at census block, which is the lowest level of census geography, it will not be able to compare the statistical model in terms of block level.

Even though the quality of UCR type data primarily depends on how police departments report to, this study only utilizes the UCR type crime , and addresses the variation of homicides across the neighborhoods of the city. Due to the strict rules and procedures of maintaining UCR type crimes, the police department must have much more accurately records on such crimes in their database.

Due to changes with crime recording systems (UCR & NIBRS) in U.S., this study has to limit itself to certain period of time (e.g. from 1990 to 1999 for the City of Richmond). That is, it would be able to work with consistent and comparable crime data over the years. That becomes like a trade off between crime data quality and the length of study period. Since the numbers of years are fairly enough to construct a longitudinal research, the study determines UCR as meeting all other expectations of this study.

Rather than technical constraints of secondary data, this study is much more concerned about whether the Police department can be willing to share their crime data or not for a long period of time. Accordingly, accessibility to the official crime data for the specific time period has become problematic to determine the scope of this study in terms of neighborhood crime types. This study could only be allowed to access for homicide incidents data, and therefore limited to homicide only.

Moreover, this study is limited to the Census geography as spatially analyzing the neighborhood homicide and social disorganization. Nonetheless, the boundaries of Census geography coincide with the administrative boundaries within the city as this study can access very comprehensive data for the contextual characteristics of neighborhoods. On the other hand, census geography might not be utilized to spatially compare the neighborhoods from 1990 to 1999 unless they are appropriately normalized.

Finally, the present study is conceptually limited to the following points;

- Limited to SDT instead of integrating another theory
- Limited because of disregarding the situational factors as it explores neighborhood homicide variation over time.
- Limited to only two census decennial years to capture the change over time. It is, therefore, limited to linear interpolation to calculate the structural covariates of other years between 1990 and 1999.

Again, the main conceptual focus of this study is for Social Disorganization Theory.

- Limited because it cannot include intervening dimensions of social disorganization. It could not construct any other proxies to cover mediating impact of collective efficacy in terms of friendship/local networks, volunteer organizations, and unsupervised teenage peer groups. However, residential stability (lower residential turnover) and youth variables might compensate the lack of these in some degree.

Chapter 4

Findings and Analyses

Overview

This chapter primarily aims to construct the entire data set, thoroughly analyze it for the purpose of the study, and systematically test the hypotheses with respect to Social Disorganization Theory.

First, this study prepares the essential data set including neighborhood social disorganization variables and homicide as a neighborhood crime. Then, it summarizes the individual variables with respect to elements of descriptive statistics, such as central tendency and measurement of dispersion, for 1990 and 1999. Then, this study computes all other structural covariates for other years between 1990 and 1999. It uses linear interpolation for the calculation. In terms of neighborhood homicide preparation, this study performs many geocoding procedures to convert the incidents' addresses into geographic points in GIS (Geographic Information System) framework.

Second, this study visualizes the distribution of neighborhood social disorganization variables across the geography, and illustrates essential thematic maps (classified by standard deviations) to better comprehend the changes in the City of Richmond from 1990 to 1999.

Last, this study constructs factors (principle components) for residential mobility and low SES. Then, it includes these latent (unobservable) variables with the rest of variables into the multivariate statistical models.

Since homicide incidents are rarely observed across the neighborhoods in the City of Richmond, this study need to approach the research problem as seriously taking such rareness into consideration. That is, it avoids from rareness across the neighborhoods and insufficient variation within the homicide (dependent variable) to best fit the model by any regression models that work with a DV at continuous level of measurement. On the other hand, most homicides in the neighborhoods are significantly clustered in certain part of the city. It, therefore, allows the study to distinguish the neighborhoods into two groups such as the ones having homicide and the ones having no homicide. For the sake simplicity and robustness, this study, therefore, constructs *binary logistic regression* models to explore the changes in the original *odds* of neighborhood homicides in relation to structural covariates of neighborhood social disorganization for each separate year and 10 years together.

In the longitudinal setting, this study also constructs difference models with Multinomial Logistic Regression (MLR) analyses as it explores the changes in the original odds of neighborhood homicide *increase* associated to the increases in structural covariates over the years. In fact, this study recodes the change in homicide rates for essential year ranges to test its hypotheses. After recoding, dependent variable (e.g. change in homicide rate) does have three categories such as “no change”, “decrease”, and “increase” for constructing MLR. The neighborhood level predictors in MLR are still determined at ratio level of measurement.

However, this study still acknowledges the potential spatial autocorrelation, and copes with Moran’s I statistics. Once it determines the neighborhoods having homicide hotspot(s) over the years, and visualizes in GIS environment, this research makes sub-selection of these neighborhoods to deeply focus on the associations between homicide and neighborhood social disorganization over all. Briefly:

- This study employs binary logistic regression to assess the changes in the original odds of homicide, as a neighborhood crime for each year, since homicide incidents are recognized as rare events in the neighborhoods.
- For assessing the change over each two essential time steps, this study utilizes Multinomial Logistics Regression (MLR) analysis for categorical dependent variable with three different categories such as increases, decreases, and no changes over time.
- Similarly, MLR has been the promise to assess the change within both rare neighborhood homicide and social disorganization over the years.
- Based upon the homicide hotspot analysis, this study targets certain neighborhoods to suggest any specific policy considerations.

Data Preparation for Neighborhood Social Disorganization

Census Raw variables

This study uses 22 (Twenty two) different census variables extracted from both online Census web site and GeoLytics data reservoir (see Appendix A). Notably, each census variable might have different universe (denominator for correctly computing the percentages), and the researchers have to use appropriate universe for calculating actual percentage variables in their studies. And, they would be able to have correctly normalized the variables. This becomes more important to construct statistical models and to compare these variables over time. In this line of reasoning, the researchers are supposed to normalize their raw variables extracted from different resources so as to conveniently compare the neighborhoods and their relative differences over time.

Therefore, the Table 4.1 includes short abbreviations of the twenty two census variables, their brief explanations, and their conveniently unique universes. Since the unit of analysis is census block group as a neighborhood proxy, raw census variables are all extracted and calculated at the census block group level for the City of Richmond. These variables are clearly shown in Table 4.1 below:

Table 4.1: Raw Census* Variables, Explanations, and Their Universe**

VARIABLE	**BRIEF EXPLANATION**	*UNIVERSE*
TOT_POP	Total population	-
TOT_HHOLD	Total households	-
TOT_FAMILY	Total number of families	-
TOT_HOUSING	Total housing units	Total housings
POP16_OVR	Total population 16+ years	Total population
TOT_POVERTY	Total population for whom poverty status is determined	-
TOT_LABOR_FORCE	Total 16+ population in labor force: male and female together	Total 16+ population
H_OCCUPIED	Total housing units: occupied	Total housings
POP_5_OVER	Residents living 5 years and over…	-
POP_5_DIFF	Residents live 5+ years in different house	Residents living 5 years and over…
H_RENTER	Total occupied housing units: renter occupied	Total housing units: occupied
RACE_NHWHITE	Non-Hispanic Whites include Whites that did not indicate Hispanic origin	Total population
RACE_BLACK	African Americans include people who identified themselves as Black regardless of Hispanic Origin	Total population
RACE_LATINO	Latinos include Whites of Hispanic Origin and Others of Hispanic Origin	Total population
RACE_API	Asian/Pacific Islanders include Asians, Native Hawaiians and Other Pacific Islanders, regardless of Hispanic Origin	Total population

RACE_OTHER	Others include those who identified themselves as Others of Non-Hispanic Origin and American Indians	Total population
FHNHP_OWN	Female-Headed Households No husband Present: Own Children <18	Total families
POVERTY_BLW	Population below poverty line	Total population for whom poverty status is determined
HHOLD_PAI	Total households: with public assistance income	Total households
CIVIC_UEMP	Total civilian labor force unemployed: male and female together	Total population 16+ years
YOUTH	Youth population include males and females between 12 and 24 ages	Total population
H_VACANT	Total housing units: vacant	Total housings

* Source : Census 1990 and 2000, SF3 codebooks
** Universe : Denominator for each Census variable.

<u>Linear Interpolation Technique to Compute Structural Covariates Between 1990 and 1999</u>

This study takes the structural covariate differences between Census 1990 and 2000 into consideration so as to understand the structural changes in the City of Richmond. Although it might be considered a constraint to use only two census years in some degree, this study also calculates the scores of structural covariates of other remaining years between Census 1990 and 2000. It determines to run linear interpolation technique to assess these scores, and posits using these scores to systematically capture the changes in neighborhood social disorganization over the years. For the interpolation, raw scores of each census variable (presented in Table 4.1) are calculated for each neighborhood (N=163 neighborhoods in the City of Richmond) and eight more years. Then, the percentages and actual proxy variables for neighborhood social disorganization are computed. Notably, this study prefers to use the year 1999 instead of 2000 since

Census 2000 data were actually collected in 1999 and distributed online in 2000 (Census codebook, 2000).

This study, therefore, runs linear interpolation to calculate all other raw social disorganization values in the neighborhood between year 1990 and year 1999. For the linear interpolation, this study constructs the following mathematical equation, and reliably computes the raw scores in Microsoft Excel Spreadsheet;

Equation 4.1: Linear interpolation equation to compute the census scores for the years between 1990 and 1999.

$$Y = N * [(YEAR\_99) - (YEAR\_90)] / 9 + YEAR\_90$$

N: 0 = YEAR_1990
1 = YEAR_1991
2 = YEAR_1992
3 = YEAR_1993
4 = YEAR_1994
5 = YEAR_1995
6 = YEAR_1996
7 = YEAR_1997
8 = YEAR_1998
9 = YEAR_1999

Y is a new value calculated by the linear interpolation equation. It is basically the linear mathematical equation that can be constructed if two points are already known in algebra. In the interpolation, we calculate new scores (22*163*8) for 22 census variables, 163 neighborhoods and 8 years between 1990 and 1999. In fact, the Microsoft Excel should be considered the best tool to construct such 22*163 formulas and calculate the scores of the remaining years. Once calculating them by the linear interpolation, these scores have been transferred into SPSS software environment.

Again, this study identifies and compares the percentage values of each raw variables in terms their central tendency values and other general descriptive statistics before calculating actual proxies for the social disorganization in the following sections. In fact, the percentage variables are used to calculate the actual proxies for social disorganization variables in this study. Some are computed with respect to their percentage values, whereas some are used to construct certain factor loadings and/or indexes for certain social disorganization variables. For instance, race/ethnic heterogeneity is specifically calculated by interaction index as discussed in previous chapter. Nevertheless, the tricky part for calculating race/ethnic heterogeneity is how to correctly classify the race/ethnic groups in this study.

In fact, direct classifications of racial/ethnic groups according to the Census variables is more likely to be problematic because of the fact that the Census Bureau has made some changes in gathering data from 1990 to 2000. That is, the researchers need to take the overlaps of Hispanic origin and race into consideration so as to obtain mutually exclusive categories in both 1990 and 2000. In this line of reasoning, this study has utilized a classification methodology commonly preferred in the previous research to precisely operationalize the racial/ethnic groups in the Census. Accordingly, this study constructs 5 (five) different groups to correctly classify race and ethnicity. These include Non-Hispanic white, Black (African American), Latino, Asian-Pacific-Islander (API), and other.

<u>Descriptive Statistics for Neighborhood Disorganization</u>

This section calculates percentage values of each raw census variable, identifies, and compares them for the year 1990 and 1999. Clearly, the essential census variables in this study are all measured at ratio level. It is, therefore, confidently enough to examine their distribution with respect to the central tendency and dispersion values. In fact, mean and/or median values represent their variables for the neighborhoods in the city. Since this study deals with only two main census years, it prepares a composite table covering each variable's descriptive statistical values for each census year. Accordingly, it realizes the overall changes of population, households, and housing conditions in the City of Richmond from 1990 to 2000. In the city, there are N = 163 cases (neighborhoods)

Apparently, the Table 4.1 guides this study how to calculate the percentage value for each census variable with appropriate universe. Each calculation and descriptive statistics have been performed by SPSS, and reported with composite tables below to systematically compare them. Detailed SPSS output tables are also included in the Appendix B. This section only looks for the change between 1990 and 1999 since they are the primary time steps, and the change argument in this study is simply based on such two decennial census years.

For the central tendency, mean (Table 4.2) and median (Table 4.3) together are preferred, whereas standard deviation is examined for the dispersion of their distributions. Once composite tables are separately constructed for mean, median and standard deviation, they are evaluated together to better understand the change in both central tendency and dispersion between these two decennial years.

Table 4.2: Mean Values* of Census Variables (Structural Covariates) for 1990 & 1999

VARIABLE	**YEAR 1990**	*YEAR 1999*
PR_DIFF	25.27%	50.00%
PR_RENTER	50.22%	50.37%
PR_NHWHITE	41.14%	36.05%
PR_BLACK	57.15%	59.30%
PR_LATINO	.61%	1.95%
PR_API	.85%	1.11%
PR_OTHER	.28%	1.59%
RACE_HTRG	.26%	.28%
PR_FDISTRUP	32.53%	20.72%
PR_POV_BLW	18.36%	21.63%
PR_HHLD_PA	11.45%	5.30%
PR_UEMP	4.21%	5.31%
P_DENSITY	5550.62 persons/ $mile^2$	5292.83 persons/ $mile^2$
PR_YOUTH	18.03%	18.28%
PR_VACANT	9.73%	9.02%

* Over 163 neighborhoods in the City of Richmond (See Appendix B).

According to the mean Table 4.2, the neighborhoods in the City of Richmond have structurally changed in terms of the census variables above. Some structural covariates indicate little changes, but some have larger changes from 1990 to 1999. In fact, with respect to the mean, the largest change has been experienced for the percentage of residences living in different houses, whereas the lowest change (almost stable) has examined for the percentage of renter occupied housings in the City of Richmond. The households in the City of Richmond might have been more mobilized from 1990 to 1999. Renter occupied housings and its change may not address everything about the mobility in the City of Richmond.

Table 4.3: Median Values* of Census Variables for 1990 & 1999

VARIABLE	*YEAR 1990*	**YEAR 1999**
PR_DIFF	23.38%	49.96%
PR_RENTER	48.26%	49.28%
PR_NHWHITE	33.40%	23.70%
PR_BLACK	64.90%	66.21%
PR_LATINO	0	0.49%
PR_API	0	0
PR_OTHER	0	1.22%
RACE_HTRG	.25%	.26%
PR_FDISTRUP	20.13%	18.86%
PR_POV_BLW	14.89%	19.21%
PR_HHLD_PA	8.20%	3.52%
PR_UEMP	3.72%	3.78%
P_DENSITY	4525.59 persons/ mile^2	4536 persons/ mile^2
PR_YOUTH	16.56%	17.25%
PR_VACANT	8.48%	7.74%

* Over 163 neighborhoods in the City of Richmond (See Appendix B).

As seen in the Table 4.3, the distribution of each variable is quietly skewed since mean values and median values are different than each other. In fact, the most skewed distribution belongs to Family disruption (Female-Headed Household No Husband Present with own children less than age 18). To better comprehend the distribution of each structural covariate in the City of Richmond, this study had better look at standard deviation to reveal the degree of dispersion for each variable.

Although mean of each remained almost the same, their dispersions have changed over time as seen in the Table 4.4. Therefore, their geographic distribution might have changed over time. To make sure about the actual changes in these variables, it is sensible to look at median and standard deviation values of each variable as well as the changes over these two decennial years.

Table 4.4: Standard Deviations* of Census Variables for 1990 & 1999

VARIABLE	YEAR 1990	YEAR 1999
PR_DIFF	8.46%	14.57%
PR_RENTER	31.52%	25.61%
PR_NHWHITE	34.97%	34.30%
PR_BLACK	35.74%	34.96%
PR_LATINO	.93%	3.45%
PR_API	1.84%	1.96%
PR_OTHER	.49%	1.81%
RACE_HTRG	.19%	.20%
PR_FDISTRUP	37.14%	15.93%
PR_POV_BLW	15.30%	16.16%
PR_HHLD_PA	11.00%	6.14%
PR_UEMP	3.04%	5.32%
P_DENSITY	4111.92 persons/ mile^2	3894.46 persons/ mile^2
PR_YOUTH	11.73%	13.45%
PR_VACANT	6.85%	7.28%

* Over 163 neighborhoods in the City of Richmond (See Appendix B).

In considering the values of central tendency and dispersion of distribution together;

- Mean and/or median, as central tendency values, increase for *the percentage of residences who lived in different houses*, so does its standard deviation, as a dispersion value around the mean, increase from 1990 to 1999. In fact, as mean value increases over years, neighborhoods' residences living in different houses might have become more dispersed across the city in 1999.
- Mean and/or median remain almost the same for *the renter occupied housings* over the years, whereas standard deviation around the mean decreases from the census 1990 to 1999. It might be confident that neighborhoods' renter occupied housings might have become less dispersed around the mean in 1999.

- Mean and/or median decrease for *the percentage of white population*, as standard deviation remains almost the same from the census 1990 to 1999. Neighborhoods might have shown similar dispersion in both 1990 an 1999.
- Mean and/or median little increase for *the percentage of black population*, as standard deviation remains almost the same from the census 1990 to 1999. Neighborhoods' scores of the black population might have shown similar dispersion in both 1990 an 1999.
- Both central tendency and dispersion values remain almost the same for *the race/ethnic heterogeneity* from 1990 to 1999. Interestingly, the City of Richmond has only two primary race/ethnic groups such as white and blacks. Other groups have no significant portions in calculating the heterogeneity. Accordingly, the race/ethnic heterogeneity may not provide the statistical models with enough variability to explain the change in neighborhood homicide over the years.
- Central tendency values decrease for *the percentage of family disruption* in some degree, as its dispersion around the mean sharply decrease from 1990 to 1999. In fact, the scores of the family disruption variable have become more homogeneous in 1999 as compared to 1990.
- As central tendency values increase for *the percentage of population determined below the poverty line*, its standard deviation value remains almost the same from 1990 to 1999.

- The mean/median values of *the percentage households receiving public assistance* dramatically decrease, so does the standard deviation. People in the City of Richmond might have received lee public assistance over the years. The scores of this structural covariate have become more homogenous in 1999.
- Although the central tendency of the distribution remains almost the same for *the percentage of labor force unemployed*, its standard deviation dramatically increases. In fact, the scores of this structural covariate have become more heterogeneous in 1999.
- Although the central tendency of the distribution remains almost the same for *the population density*, its standard deviation dramatically decreases. In fact, the scores of this structural covariate have become more homogeneous in 1999.
- Both central tendency and dispersion values have increased for *the percentage of youth population* in some degree. In fact, the scores of the distribution have become more heterogeneous in 1999.
- Although mean/median values decrease for *the percentage of vacant buildings*, its standard deviation increases in some degree. This might be thanks to the city investments on neighborhood development during the study period of time. Therefore, the scores of vacancy rate have become more heterogeneous in 1999.

Taken together, structural covariates have changed from 1990 to 1999 with respect to both central tendency of their distributions and measures of their dispersion. This study, therefore, takes such changes into consideration as it explores the association between the change in neighborhood crime and the change in neighborhood social disorganization over the years. That is, it calculates the structural covariates of the remaining years between 1990 and 1999 by running linear interpolation. However, it just reports the percentage values of structural variables for years 1990 and 1999 since these are the main time steps for structural changes. The remaining years between them will have got linear values between them. As seen in the central tendency and dispersion values, however, these covariates across the neighborhoods might have shown different patterns over the years. Direction of linearity might be different for different neighborhoods over these two decennial years. Accordingly, this study is able to construct different multivariate statistical models for different years and year ranges.

This study, on the other hand, needs to compute two composite variables to operationalize SES and Residential Mobility. The next section briefly notes how and which technique is utilized to calculate these composite variables as much as previous studies have done to test Social Disorganization Theory.

Factor Analysis Constructing SES and Residential Mobility Factors

This study includes the percentage of renter occupied housings and the percentage of residences living in different houses in last five years while it employs them as the proxies of *residential mobility*. Likewise, this study combines three different structural variables to operationalize the *SES* such as the percentage of population determined below the poverty line, the percentage of the households having public assistance, and the percentage of labor force unemployed. For both residential mobility and the low SES, this study uses factor analysis as an analytical technique to establish these essential composite variables.

Factor analysis is primarily utilized to identify the underlying processes that can explain a set of certain variables (Tabachnick and Fidell, 2001). It, therefore, allows the researches to explore the certain degree of measurement overlaps, and to reduce the number of many variables in the working data set. In fact, factor analysis determines how some variables are clustered, and establishes few unobservable variables instead of many observable variables. Clearly, factor loadings might also avoid from potential multicollinearity threats when such these highly correlated variables are included in the same statistical models. Accounting the underlying structure among these variables might become more important if the researchers study in the longitudinal setting. In longitudinal approach, factor loadings, or principle components, provide consistent variability of the composite variables since they do only share the commonalities, not error variability (Mertler and Vannatta, 2003). Accordingly, factor loadings are frequently employed to establish consistently reliable composite variables for further uses in various regression equations such as logistic regression.

In terms of assumptions, Tabachnick and Fidell (2001) posit that principle components analysis is very flexible when they are used as an exploratory purpose to reduce the number of variables in the data set, not when confirmatory purposes. This study, therefore, disregards checking the assumptions since the principle components are just used to establish some composite variables. In fact, its primary objective is to identify and summarize the variation of several variables that are correlated to each other.

Mertler and Vannatta (2003: 250) state four criterions to establish reliable factor loadings. First, these components, or factor loadings, are supposed to have at least 1 (one) or more eigenvalue. Otherwise, they cannot be issued as a composite variable of many other observable variables. The eigenvalue determines the total amount of variance shared by each component, or factor. Second, scree plot should be examined for the magnitude of each eigenvalue. Scree plot also allows the researchers to identify the appropriate number of components as they realize sharply enough drops for each scree plot. In relation to scree plot, third criterion is to decide how many factors should be kept in the analysis. According to the Mertler and Vannatta (2003), the researchers should only keep the factors accounting for at least 70% of the total variance. Final criterion to retain certain components is to include the model fit. Commonly, if the degree of correlations between variables and the components remain at .05 or less significance level, the factors are considered reliable. In addition to these criteria, the researchers should also review the percentage of residuals remaining to reproduce more components. In fact, the researchers would like to minimize the number of residuals with the components.

Residential mobility factor is constructed by both Percentage persons living in different house and percentage of renter occupied housings as shown in the Table 4.5.

This table also informs how much residential mobility factor (component) accounts for each variable included in the factor analysis.

Table 4.5: Communalities of the Variables for Residential Mobility

	Extraction for 1990	***Extraction for 1999***
PERCENTAGE PERSONS LIVING IN DIFFERENT HOUSE	.704	.793
PERCENTAGE OF RENTER OCCUPIED HOUSINGS	.704	.793

Extraction Method: Principal Component Analysis.

Residential mobility factor accounts for 70.4% of variance of the variables in 1990, whereas it accounts for 79.3% in 1999 (Table 4.5). In fact, these scores are well enough to construct composite variables based on these variables for each Census year. According to total variance explained by each component below (Table 4.6), this study has captured only one acceptable factor loading with the Eigenvalue of 1.408 > 1 for the Census year 1990 and Eigenvalue 1.586 > 1 for 1999. That is, one factor captures the majority of the variation for these variables. In this case, the percentage of commonalities and total variance explained by the factor is the same since there are only two variables included to establish the factor. Scree plot does not provide additional information about the factors since the residential mobility is constructed by only two variables.

Table 4.6 provides Eigen values and percentage of total variance that is explained by the residential mobility factor for the variables included. This study, therefore, looks at these scores and determines whether the factor is acceptable or not.

Table 4.6: Eigen Values and Percentage of Variance Explained by the Residential Mobility Component

	Year 1990	***Year 1999***
Eigen Value	1.408	1.586
Total Variance Explained	70.4%	79.3%

According to the Table 4.7, for the Factor loadings, the residential mobility component has strong and positive loadings by the variables. Each variable loads almost 84% of their variability for this component in 1990, 89% of their variability in 1999. On the other hand, this study further needs *factor scores* so as to include the residential mobility as a composite variable in its statistical models. SPSS generates these scores through different versions. Among the ways how SPSS generates factor scores, this study, therefore, uses regression coefficients as new values of the residential mobility in the data set.

Table 4.7 shows how strong loadings the residential mobility factor can do for each variable.

Table 4.7: Residential Mobility Factor Loadings

	Component for 1990*	***Component for 1999****
PERCENTAGE PERSONS LIVING IN DIFFERENT HOUSE	.839	.890
PERCENTAGE OF RENTER OCCUPIED HOUSINGS	.839	.890

* Extraction Method: Principal Component Analysis.

Again, Table 4.8 provides Eigen values and percentage of total variance that is explained by the SES factor for the variables included. This study, therefore, looks at these scores and determines whether the factor is acceptable or not.

Table 4.8: Eigen Values and Percentage of Variance Explained by the Low SES component

	Year1990	***Year 1999***
Eigen Value	2.208	2.044
Total Variance Explained	73.6%	68.2%

The SES factor accounts for almost 74% of variance of the variables in 1990, whereas it accounts for 68.2% in 1999 (Table 4.8). The SES factor, therefore, accounts for fairly enough variation of each variable while principle component analysis is used as extraction methodology. In fact, the SES component captures the variation of almost 82% of the percentage of population below poverty line, 82% of the households having public assistance, and 57% of the unemployed individuals in civilian labor force in 1990 (Table 4.9). In the same table, the SES component captures the variation of almost 83% of the percentage of population below poverty line, 70% of the households having public assistance, and 52.4% of the unemployed individuals in civilian labor force. According to total variance explained by the SES component (Table 4.8), this study has captured only one acceptable factor loading for each year with the Eigenvalue of 2.208 > 1 in 1990 and the eigenvalue 2.044 >1 in 1999.

The SES factor is constructed by three structural covariates such as percentage of population below poverty line, percentage of households having public assistance, and percentage of unemployed individuals in civilian labor force as shown in the Table 4.9. This table also informs how much residential mobility factor (component) accounts for each variable included in the factor analysis.

Table 4.9: Communalities of the Variables for the low SES

	Extraction for 1990*	***Extraction for 1999****
PERCENTAGE OF POPULATION BELOW POVERTY LINE	.816	.825
PERCENTAGE OF HOUSEHOLDS HAVING PUBLIC ASSISTANCE	.822	.695
PERCENTAGE OF UNEMPLOYED INDIVIDUALS IN CIVILIAN LABOR FORCE	.570	.524

*Extraction Method: Principal Component Analysis.

According to the Table 4.10, for the Factor loadings, the SES component has strong and positive loadings by the variables. Each variable loads more than 70% of their variability for this component. The percentage of population below poverty line and the households having public assistance load almost 90% of their variability, whereas the unemployed individuals in civilian labor force does almost 76% of its variability in 1990. In 1999, on the other hand, the percentage of population below poverty line loads almost 91%; the households having public assistance loads 83.4%; whereas, the unemployed individuals in civilian labor force does load 72.4% of its variability in 1999.

Table 4.10 shows how strong loadings the SES factor can do for each variable.

Table 4.10: The Low SES Factor Loadings

	Component* for 1990	***Component* for 1999***
PERCENTAGE OF POPULATION BELOW POVERTY LINE	.903	.909
1990 PERCENTAGE OF HOUSEHOLDS HAVING PUBLIC ASSITANCE	.907	.834
1990 PERCENTAGE OF UNEMPLOYED INDIVIDUALS IN CIVILIAN LABOR FORCE	.755	.724

* Extraction Method: Principal Component Analysis.

Accordingly, this study successfully establishes the essential composite variables for the purpose of neighborhood social disorganization. After this point, it utilizes these composite variables in the following analytics instead of many variables already utilized to construct them. It, therefore, geographically describes the following variables that are the only variables to be further focused in this study: Residential mobility, racial/ethnic heterogeneity, family disruption, SES, population density, youth, and vacancy.

Descriptive Maps for Neighborhood Disorganization in 1990 and 1999

Descriptive maps below might provide the readers with better sense as they visually evaluate the central tendency values. In fact, spatial analysis by GIS (Geographic Information Systems) software allows the research to geographically describe the neighborhoods in terms of mean, standard deviation, and their relative scores on the maps. Such thematic approach in the following sections, therefore, better visualizes structural differences across the neighborhoods. Some neighborhoods might keep remaining above the mean, whereas others do below the mean. While geographic distributions of the neighborhoods might change according to certain disorganization variables from 1990 to 1999, some of their geographic distributions remain similar. Accordingly, this study takes the advantages of thematic mappings with respect to the standard deviations as it performs descriptive statistics (central tendency values) to contextually and statistically comprehend the general distribution of the neighborhoods in both 1990 and 1999.

Thematic mappings with specific ranges above or below the mean are intentionally colored from blue to red. The white color just represents the mean of the neighborhood disorganization. Red color is consistently preferred for the higher degree of neighborhood social disorganization with respect to certain variable, whereas blue color is chosen for lower degree of neighborhood social disorganization. In fact, the researchers and decision makers would be able to concentrate on the red (hot) neighborhoods as the most problematic ones, while they would realize the less problematic neighborhoods with respect to the degree of social disorganization. This study, therefore, keeps using the same color range for thematic crime mapping and hotspot analysis through the entire research.

Accordingly, this section aims to identify and compare the neighborhoods in terms of their upper and lower standard deviation scores around the mean in map settings as follows. The advantage of describing both mean and standard deviation on maps is that one can both geographically and numerically delineate the distribution of the variables.

Figure 4.1: Residential Mobility in 1990 and 1999 (Classified by Standard Deviations from Mean)

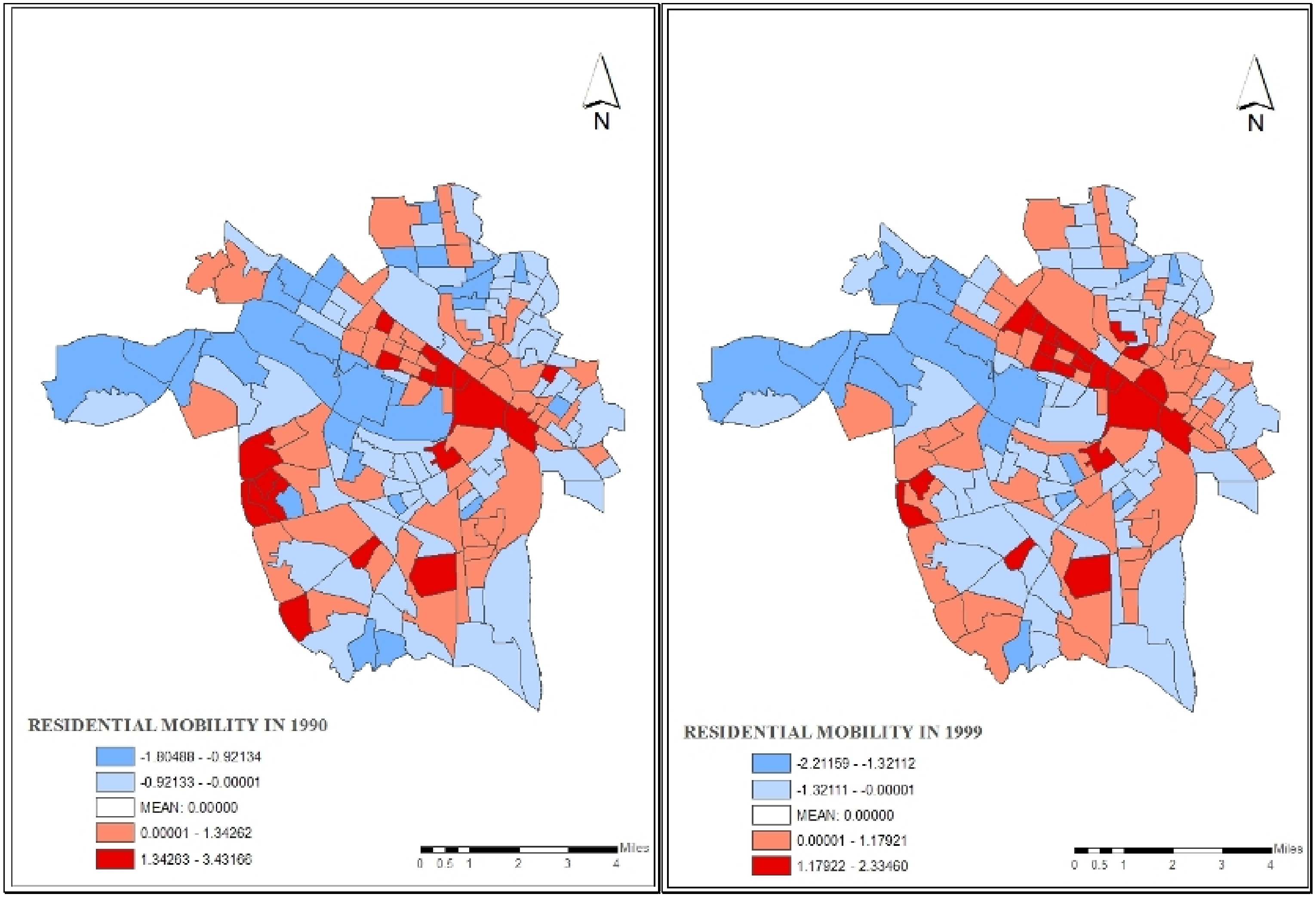


Figure 4.2: Racial/Ethnic Heterogeneity in 1990 and 1999 (Classified by Standard Deviations from Mean)

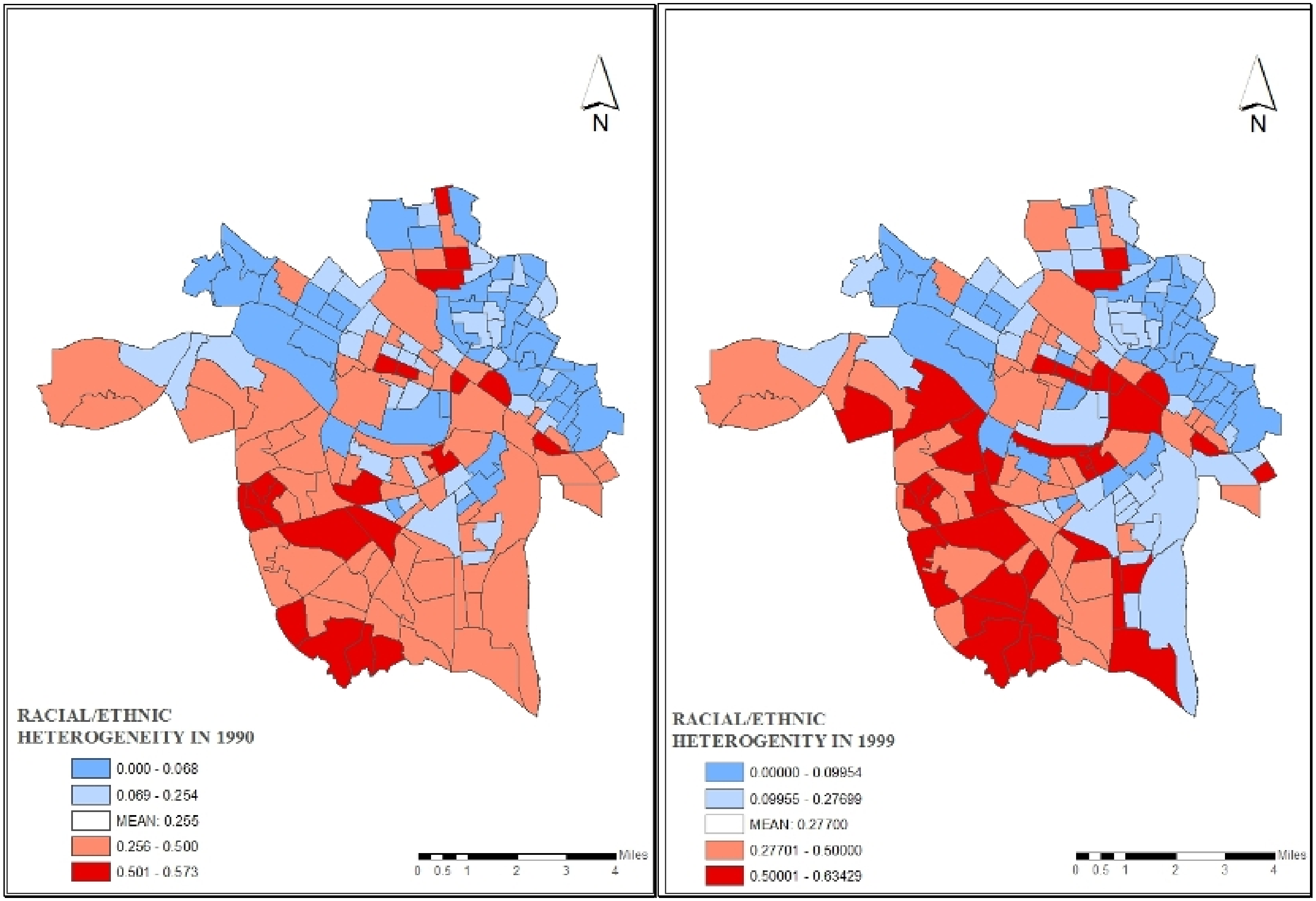
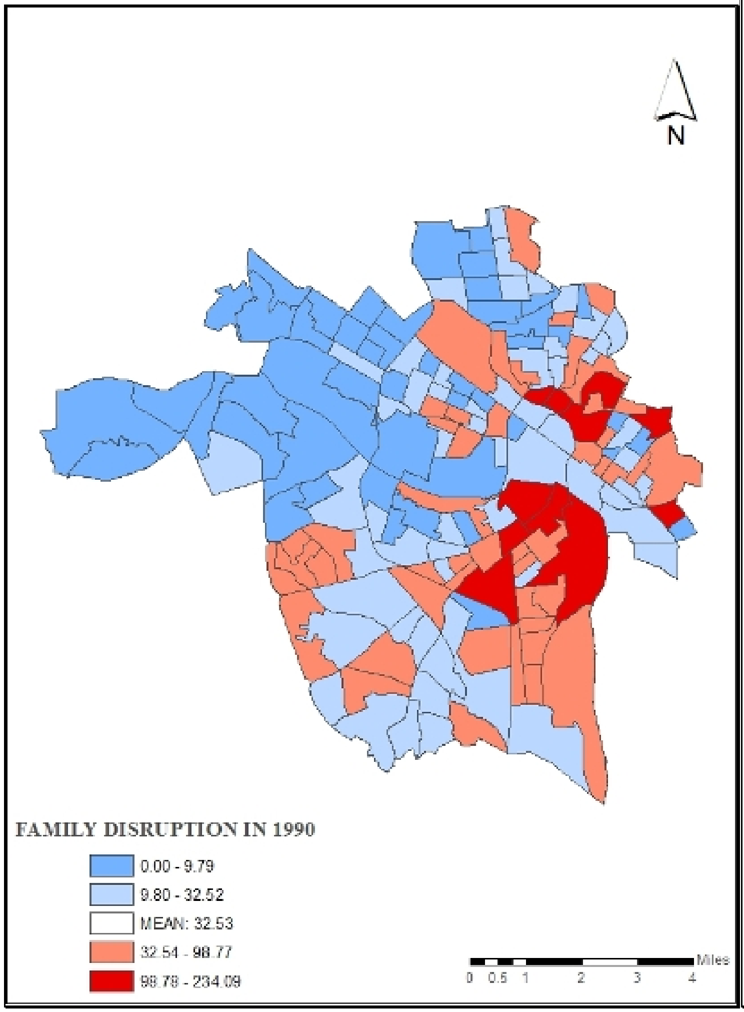


Figure 4.3: Family Disruption in 1990 and 1999 (Classified by Standard Deviations from Mean)



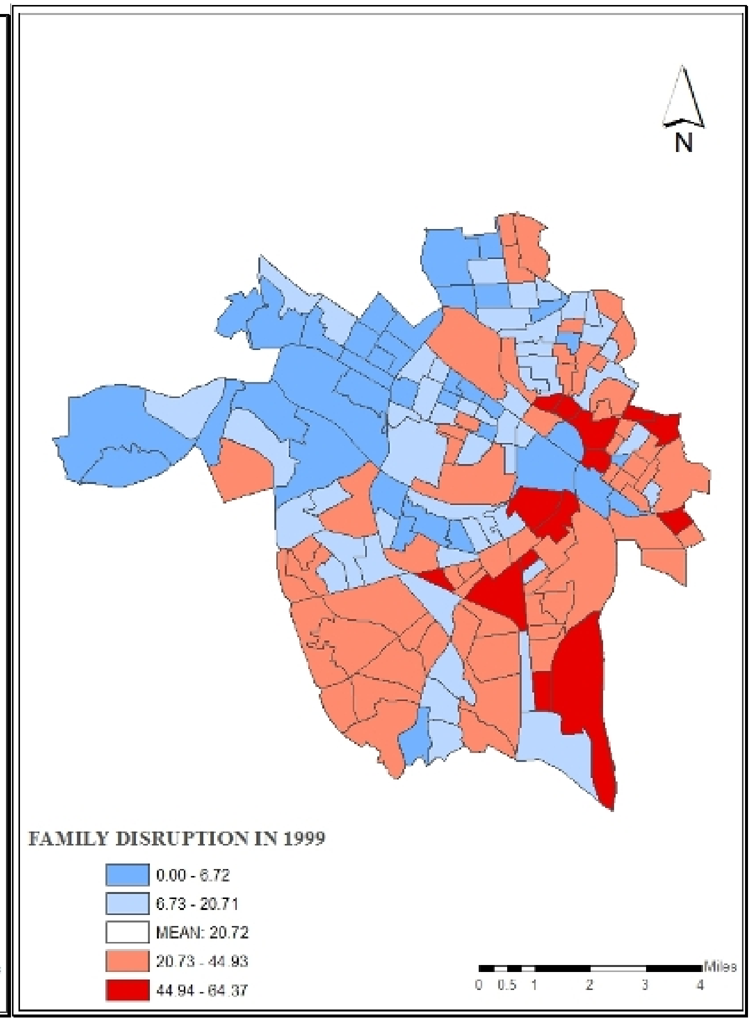


Figure 4.4: Low SES in 1990 and 1999 (Classified by Standard Deviations from Mean)

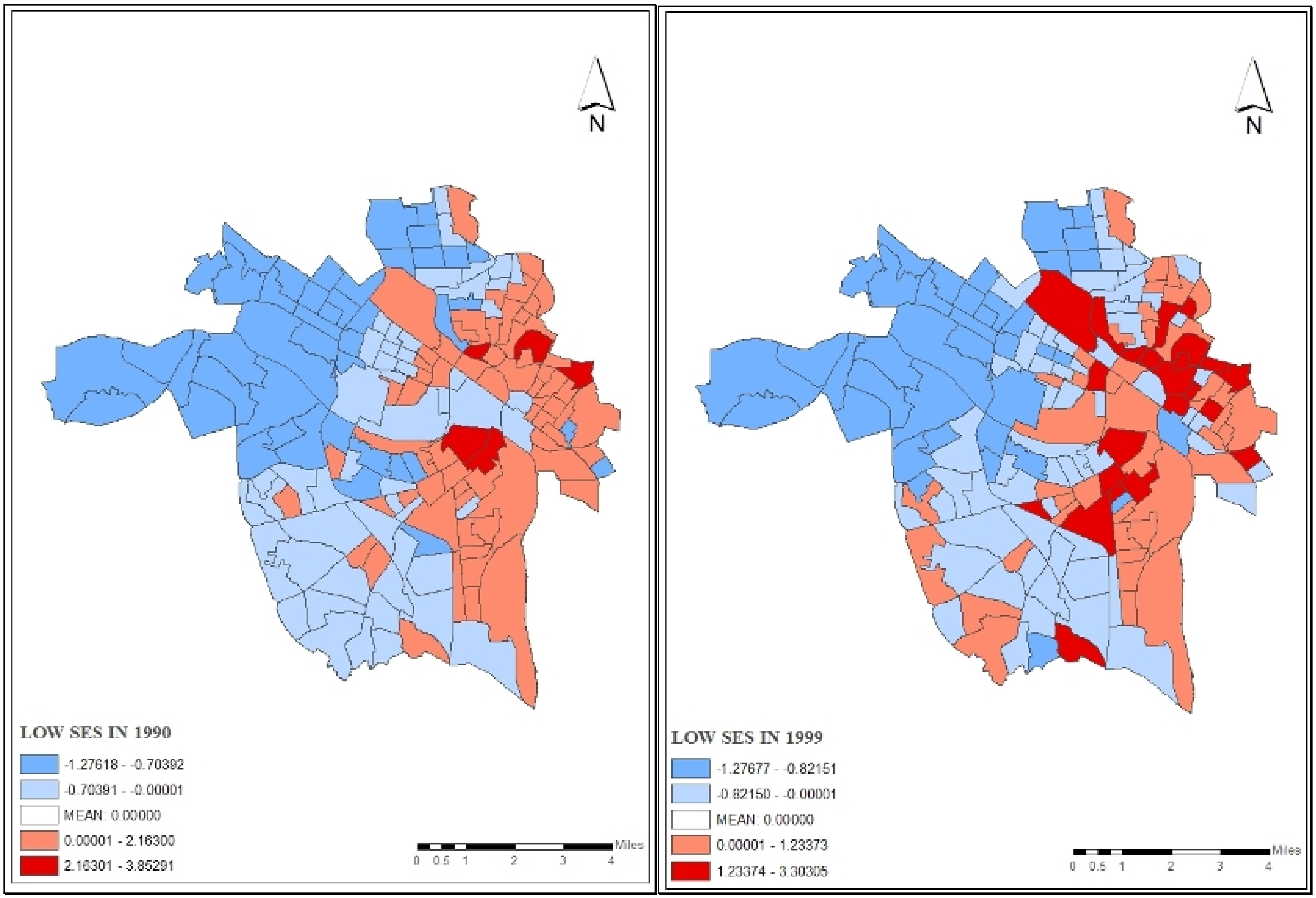


Figure 4.5: Population Density in 1990 and 1999 (Classified by Standard Deviations from Mean)

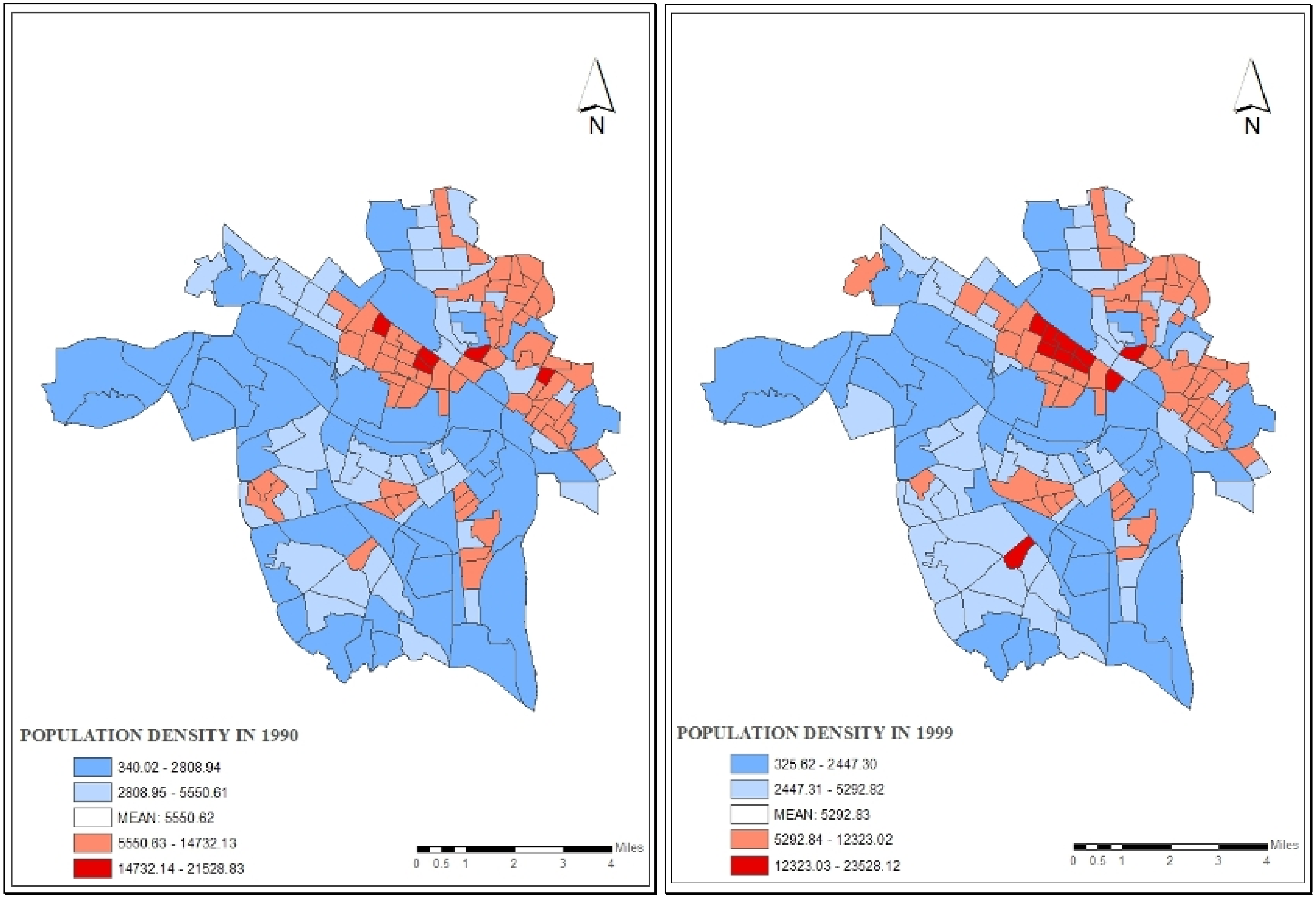


Figure 4.6: Youth in 1990 and 1999 (Classified by Standard Deviations from Mean)

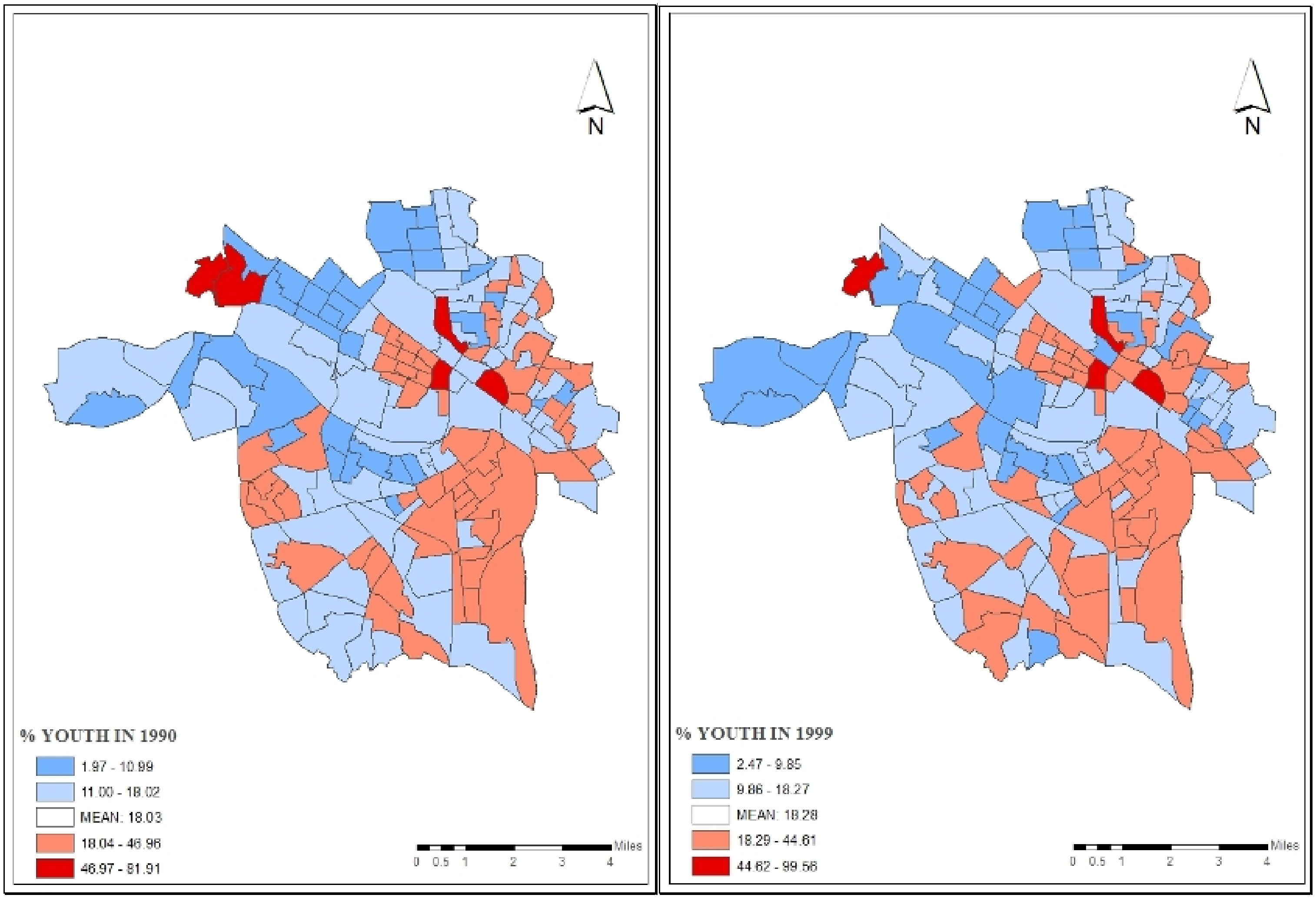
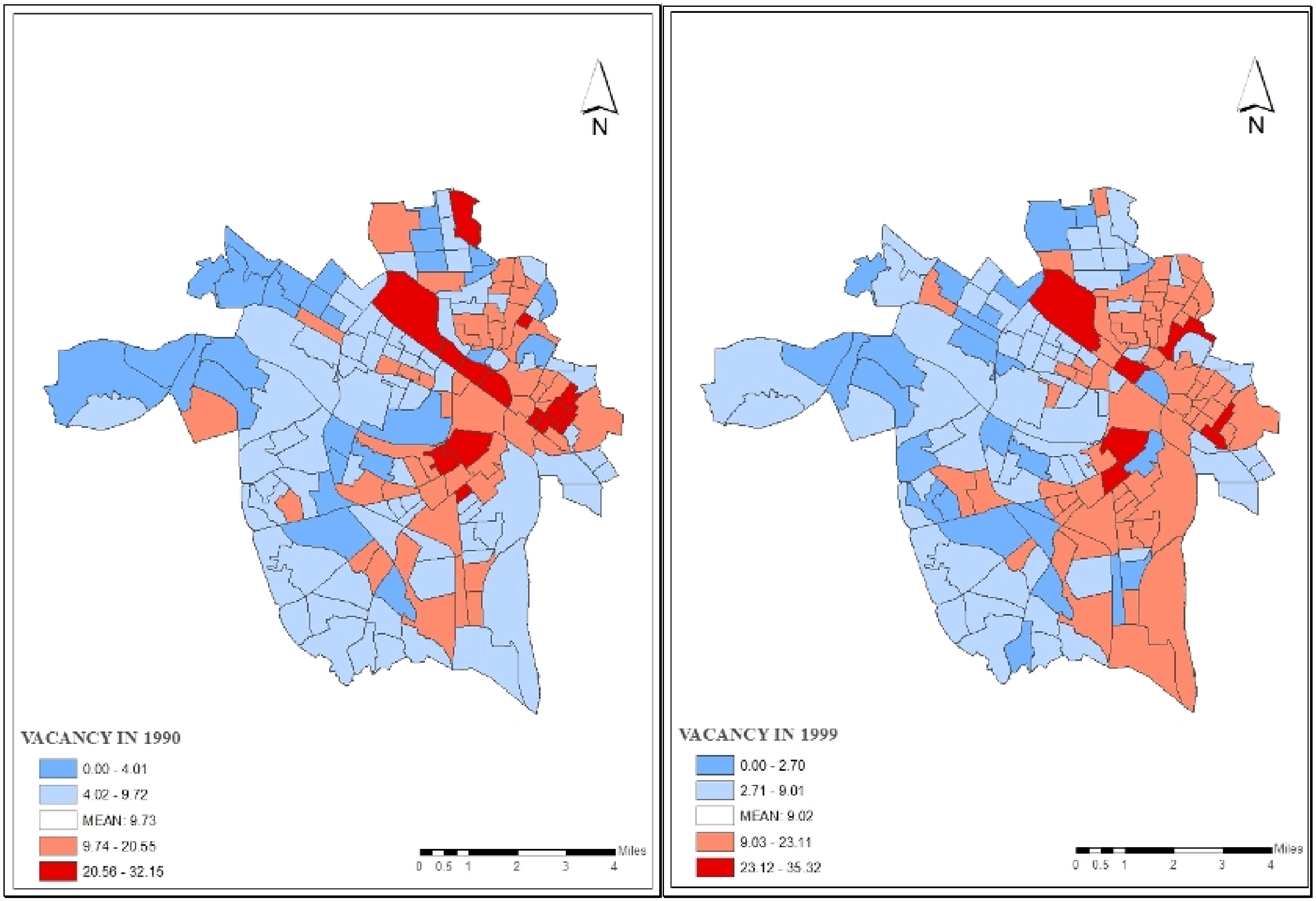


Figure 4.7: Vacancy Rate in 1990 and 1999 (Classified by Standard Deviations from Mean)



Homicide Data Preparation and Descriptive Statistics (City of Richmond)

Richmond Police Department has provided the homicide incidents data in excel format, including only certain fields such as date, street number, and street name. This study, therefore, starts to prepare the neighborhood level homicide data from scratch with qualitative explanations. Such data need to be processed and made ready for the analysis in the following steps: First, two fields (street number and street name) have been concatenated to obtain the "address" field. Street name field in original file already included the direction of the streets. Then, each homicide incidents data for each year has been converted into *.dbf files so as to open in GIS environment. This was essential step to work with geocoding engine in ArcGIS environment. This study has used ESRI Tiger street file as a reference street table to geocode the address based crime incidents. Simply, geocoding process is used to assign the proxy locations in terms of x/y geographic coordinate values for each homicide incident according to their address information. ArcGIS engine provides two main geocoding options such as automatic and interactive. Initially, I have run automatic geocoding option, and obtained certain degree of matching scores. Then, I utilized interactive options to fix address misspellings and manually match the incidents. As seen in the table below, the final matching scores are satisfactory for spatial crime analysis since the minimum matching score is more than 85%. The major issues on geocoding have occurred because of the missing directions of the streets (North, South, East, and West) for the crime incidents. If the street with the missing direction is the only street in the City of Richmond, falls in only one neighborhood, and does not corrupt the specific location of incident, then I have just matched these incidents to associated neighborhood. If street segments with missing the directions in the original file lead to suggest very much different locations across the neighborhoods, then I could not fix the problems, and leave them unmatched. Accordingly, the ultimate results are included in the table below.

Table 4.11: Geocoding Results for Homicide Incidents in the City of Richmond

YEARS	*MATCHING SCORE*
1990	94%
1991	86%
1992	90%
1993	89%
1994	88%
1995	88%
1996	91%
1997	91%
1998	95%
1999	95%

Once precisely geocoding the incidents, I have obtained *.shp file for each year of the homicide incidents. However, these are just pin-mappings, and do not provide so much information for the researchers and policy makers. Tricky part is, therefore, to aggregate such incident points (as shown below) fallen within each neighborhood across the City of Richmond. Ability to perform spatial join in ArcGIS is the way how this study has computed all counts of the homicide incidents fallen within each neighborhood. Therefore, this study has been able to calculate the number of incidents for each neighborhood. That's the purpose of the aggregation. In fact, neighborhoods with aggregated homicide information have then become ready to merge various structural covariates for further analysis and modeling in this study.

This study mainly analyzes the data set calculated and merged together by various data sets such as neighborhood homicide data, Census data for 1990 and 2000. STFID, as a unique geographic id in census data is used to merge and update all information from various data sets. In fact, these two census decennial years are the only time point to capture the trend, and change between years with respect to homicide data.

Descriptive Statistics for Homicide from 1990 to 1999

This section aims to describe the distribution of homicide counts and rate citywide over the years. It assists the study to see the big picture of the homicide distribution before going in-depth analyses.

Table 4.12 shows the number of homicides based upon the geocoded and aggregated homicide data set to the citywide.

Table 4.12: Total number of Citywide Homicide Counts in the City of Richmond

YEAR	# OF CITYWIDE HOMICIDE
1990	107
1991	101
1992	108
1993	99
1994	142
1995	104
1996	102
1997	127
1998	89
1999	70

Table 4.13 shows general descriptive statistics for the citywide homicide counts such as minimum, maximum, mean, and standard deviation in ten years.

Table 4.13: Descriptive Statistics of Citywide Homicides in the City Of Richmond

	N(YEARS)	*Minimum*	*Maximum*	*Mean*	**Std. Deviation**
CITYWIDE HOMICIDE COUNTS	10	70	142	104.90	19.462

The Table 4.13 above shows the number of incidents aggregated to the city level. In fact, there are some increases and decreases in the citywide homicide counts from 1990 to 1999. For instance, the year 1994 has the highest number of homicides, whereas the lowest score belongs to the year 1999 in the study period of time. Mean of 10 years homicide scores is almost 105 while standard deviation is 19.46. However, it is essential to examine whether a certain trend occurs or not for the homicide rates over time. The figure 4.1 below evidently designates a linear trend from 1990 to 1999 although some peak scores are experienced in some years. Again, this linear trend also justifies why this study computes the structural covariates of each year by linear interpolation technique as well as the way that it has only worked for two main time steps such as 1990 and 1999 in the City of Richmond.

Table 4.14: Descriptive Statistics for Neighborhood Homicide Rates* (See Appendix B)

	Minimum	Maximum	Mean	Std. Deviation
H_RATE_90	.00	5.07	.5885	1.02878
H_RATE_91	.00	4.20	.5263	.90378
H_RATE_92	.00	5.08	.6086	1.04427
H_RATE_93	.00	4.51	.5876	.99873
H_RATE_94	.00	7.12	.8255	1.37290
H_RATE_95	.00	9.93	.6217	1.36860
H_RATE_96	.00	8.62	.5774	1.09408
H_RATE_97	.00	9.49	.7927	1.46533
H_RATE_98	.00	6.33	.5808	1.10973
H_RATE_99	.00	5.84	.4212	.86270

* Number of homicide incidents per 1000 persons for the neighborhoods

Table 4.14 recognizes that the mean and standard deviation of homicide rate (mean: .8255; standard deviation: 1.37290) in 1994 have the highest scores over the years. The lowest mean (.4212) and standard deviation (.8627) scores are observed in 1999. Mean and standard deviation of homicide rates over years are computed based upon the neighborhoods (N=163).

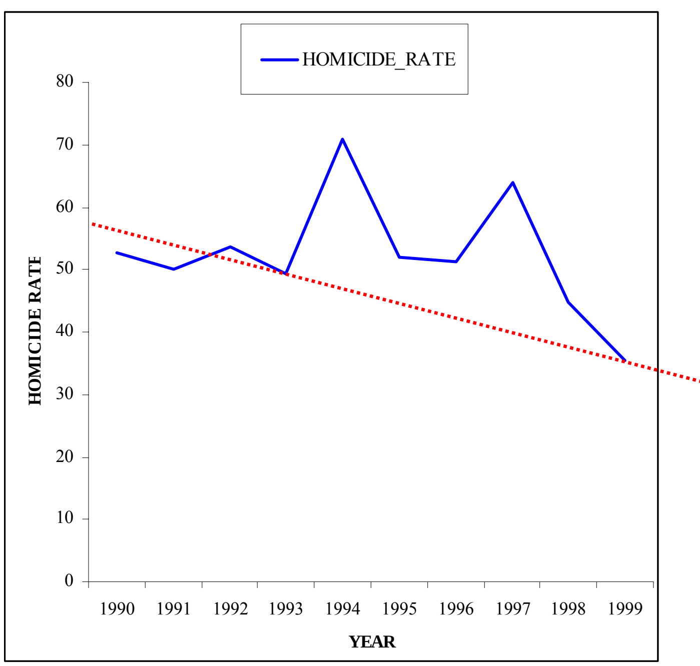
Till this point, this study has reviewed both structural covariates and neighborhood homicide counts/rates, and examined their central tendency and dispersion scores at the city level. This study, therefore, has thoroughly delineated the changes in the City of Richmond from 1990 to 1999, study period of time. It has been necessary to identify these changes across the neighborhoods for the purpose of the study. That is, different neighborhoods might have changed in different magnitudes and directions (positive or negative) over the years. Such differences should also be geographically identified in the following descriptive maps.

Trend Analysis of Citywide Homicide Rate from 1990 to 1999

This section aims to identify the general trend of homicide rates citywide from 1990 to 1999. Therefore, this study will be able to determine any inclining or declining citywide homicide rates over the years.

As seen in the Figure 4.8, homicide rates in the City of Richmond have generally decreased from 1990 to 1999. Nonetheless, the city has experienced very dramatic increases in 1994 and 1997, whereas very sharp decreases in 1995 and after 1997. In fact, the year 1994 has the highest degree of homicide rate in the entire working period of time. The second highest homicide rate was experienced in 1997. Note that 1997 was the initial date of “Project-Exile”. Although the city was not influenced by this program in the initial year, the *possible* influence of this program was realized after 1997. The city experienced almost stable degree of homicide rates in 1990, 1991, 1992, and 1993.

Figure 4.8: Homicide Trend in the City of Richmond from 1990 to 1999



Homicide rates between 1995 and 1996 also remained stable. The Figure 4.8, therefore, feasibly guides this study to determine the essentially subsequent ranges as this study constructs, therefore, well-directed difference models to reveal the change in homicide rate in relation to the change in neighborhood social disorganization.

Accordingly, this study accounts for the specific years and ranges with peak values of homicide rates, and the years where the policy programs were initiated. For instance, it is necessary to construct a difference model between 1998 and 1999 since the Blitz-to-Bloom policy program was initiated in 1999, and this study aims to investigate its contribution to predict the likelihood of having homicide across the neighborhoods. Accordingly, this study determines to focus on the following ranges to test its main hypothesis: 1990-1999, 1990-1994, 1994-1999, 1993-1994, 1994-1995, 1996-1997, 1997-1998, 1998-1999, and 1997-1999. Eventually, this study had better construct 9 (nine) difference models so as to capture all crucial ranges in which the city experienced influential homicides.

Multivariate Statistical Analysis

The City of Richmond experienced many changes in homicide rates and neighborhood social disorganization as being evidently examined by descriptive statistics and illustrative maps so far. More confidently, the previous maps to realize the changes are clearly better illustrations to comprehend which neighborhoods experienced these changes in the City of Richmond from 1990 to 1999. Nonetheless, this study is supposed to determine the best statistical techniques as it accounts the unique characteristics of homicide incidents across the neighborhoods.

Now, it is time to model (binary logistics regression model) the associations between neighborhood homicide (homicides aggregated to neighborhoods) and social disorganization for each year. Then, this study thoroughly explores the associations between the change in neighborhood disorganization and the change in neighborhood homicide by constructing Multinomial Logistics Regressions. Such an analytical strategy for this analysis makes this study utilize logistics regressions and its versions (Binary and Multinomial). Therefore, this following context attempts to justify why logistics regressions are utilized to explore the associations between neighborhood social disorganization and the original odds of having homicide in the neighborhoods, including change (difference) analysis by Multinomial Logistic Regression:

First, homicides are very rare events such that the homicide distribution based on neighborhoods is exclusively positively skewed. Because of the excessive zeros in the neighborhoods, this study concerns about non-constant error terms through both neighborhoods and years, and extreme outliers. For the sake of simplicity and robustness, therefore; this study decides to use binary logistic regressions to explore the association between neighborhood homicide and social disorganization for each year. Then, it attempts to construct likelihood model to realize how much odds of the neighborhood homicide are explained by the predictors in the binary logistics model. For the purpose of exploring the changes and constructing robust difference models over the years, multinomial logistics regression analysis becomes appropriately feasible approach to model the underlying processes of the change in both homicide and social disorganization. And, this study deals with only three categories for the changes, including "increase", "decrease", "no change".

Second, both binomial and multinomial logistic regressions are very feasible to construct robust models since they are not so conservative to specific characteristics (and assumptions) of distributions (Mertler and Vannatta, 2003). Both techniques are much more flexible than ordinary least square regressions such as multiple regressions. By these statistical techniques, this study just disregards dealing essential assumptions of OLS, and avoid from any type of mathematical transformations that might consequently make the ultimate interpretations more complicated.

Last, more than half of the neighborhoods have no homicide rates/numbers over the years. Therefore, it is confident to construct a model for the likelihood of having homicide incidents or not. For the multinomial logistic regressions, there are still three categories such that this study can assure to test the main hypothesis: Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time.

Accordingly, it is reasonable to employ the various versions of logistic regressions as analytical strategies while this study avoids from non-constant error terms and influential outliers in the data set.

In addition to why this study constructed logistics regressions, it is important to note that this study works with population data set. Therefore, significance level of the findings is not relevant for this study. This study still reports the significance levels for the readers to realize statistical significances of the findings, but it is not supposed to reject the null hypotheses as it thoroughly interprets the results. It just focuses on the alternative hypotheses and attempts to confirm the Social Disorganization Theory or not in the light of the findings.

Binomial (or binary) Logistic Regression Analysis from 1990 to 1999

Binomial (or binary) logistic regression is used when the dependent variable (DV) becomes dichotomous, whereas the set of independent variables might be different levels of measurements (Tabachnick and Fidell, 2001). Binomial logistics, therefore, just measures the probability between “0” and “1” as opposed to Ordinary Least Square (OLS) models. In logistics regression, the researchers need to interpret the changes within the original odds of the DV as one predictor alters one unit (Garson, 2007). That is, their odds ratios are known as the most common way to interpret a logit in the logistics regression model. That is, the higher/lower odds ratios than 1.000 (one) indicates the degree of contribution of each predictor to influence the odds of experiencing homicide in the neighborhoods. Regardless of lower or higher, the larger difference from 1.000 confirms the larger contribution of the predictors in the binary logistic regression models.

As described in previous sections, neighborhoods in the City of Richmond has not got equal variance within two different groups such as the ones having homicide and the ones not. With the flexibility and robustness to unequal variance within each group of neighborhoods, this study feasibly determines to utilize binary logistic regression analysis to explore the association between neighborhood social disorganization and homicide for each year. Accordingly, this study would be able to estimate the neighborhood social disorganization factors that are likely to influence the odds of homicide within the neighborhoods. Sensibly, this study can consistently determine the parsimonious logistic regression models as it repeatedly conducts the same model for ten different years in the City of Richmond. Table 4.15 includes separate binary logistic regression (LR) models for each year from 1990 to 1999. This study also constructs one more binary logistic regression model for the entire years by restructuring the variables and obtaining like growth model with binomial logistic regression.

Table 4.15: Binary Logistic Regression Models from 1990 to 1999 (See Appendix C)

YEAR	CHI-SQUARE	MODEL SIGNIFICANCE	CLASSIFICATION %	***NEGALKERGE R-Square***
1990	56.377	.000	76.7%	.402
1991	20.879	.004	69.9%	.165
1992	40.022	.000	74.2%	.296
1993	49.381	.000	77.3%	.361
New 1993	44.536	.000	74.2%	.330
1994	30.053	.000	75.8%	.301
1995	34.066	.000	73.0%	.263
1996	28.522	.000	70.6%	.220
1997	32.367	.000	67.5%	.243
1998	31.100	.000	71.2%	.240
1999	25.423	.002	74.2%	.205
ALL	**296.222**	**.000**	**71.0%**	**.234**

DV : Dummy homicide (0, 1) for each year
ALL : 163 neighborhoods have been restructured for 10 years in SPSS, and obtained with 1630 cases.
New 1993 : This model in 1993 was rerun after dropping race/ethnic heterogeneity since it had very large original odds, and overpowered the other variables' contributions in the model.

This study frames a composite table that includes Chi-square, model significance, the percentage of classification, and Nagelkerke R-square. One can determine the parsimoniousness of the logistic regression models by assessing these values in the Table

4.15. For each year, the logistic model that calculates the changes in the original odds of the homicides is significant at p = 0.05 or less. In fact, chi-square is much more than the expected value according to the number of degrees of freedom (df = 7). Degrees of Freedom (df) is different in 1993 (df = 6) and 1999 (df = 8). The percentage of classification, on the other hand, shows how much percentage of the cases (neighborhoods) are correctly classified in each logistic regression model. It can be said that the models perform fairly enough classification for the neighborhoods with respect to having homicide or not. The Nagelkerke R-square shows relatively moderate models with the values between .165 and .402 as the models fairly enough classify the neighborhoods with the predictors.

Note that, this study includes one more binary logistic regression model for the year 1993. As explained in the following context, one variable generates very inflated scores (more than 10) in the changes of the original odds of the homicide. In order to avoid from such large odds scores confounding the contributions of other variables, this study feasibly drops this variable from the binary logistic regression model in 1993. Of course, the numbers of dfs have reduced from 7 to 6 in the model, as new 1993. To inform such change for the readers, this study includes two logistic regression models such as model 1993, model new 1993 in the Table 4.15 and Table 4.16.

Table 4.16 assists the research to determine the consistency of findings with Social Disorganization Theory applied for each year. In fact, this study does only concentrate on the odds ratios to realize the actual contribution of each independent variable to influence the original odds of having homicide in the neighborhoods. The slope coefficient (B) would not be feasibly useful to interpret this likelihood since DV has just dichotomous value. Rather, interpretation of odds ratios in logistic regression is usually more intuitive than the interpretation of slope coefficient (B), as “log odds”. On the other hand, log odds are always are convertible to odds ratio in the model. That is,

$$\textbf{Odds ratio} = e^B$$

According to Table 4.16, some variables in certain years do prove the SDT, whereas some variables do not. The basic criteria is that social disorganization variables would confirm the theory if their odds ratio values are bigger than 1.00. If so; one unit *increase* in such variable influences the certain amount of percentage *increas*e of the original odds of having homicide in the neighborhoods**.** The low SES has the highest contribution to influence the changes in the original odds of having homicide in all years. Population density, on the other hand, contributes nothing to influence the original odds of homicide in the neighborhoods. Other variables perform differently in different years although the contributions of some independent variables remained consistent to influence the original odds of experiencing homicide in the neighborhoods.

Figure 4.9 illustrates how odds ratios change over the years. Race/ethnic heterogeneity in 1993 overpowered the original odds of homicide. Its inflated score might have also misled the contribution of other structural covariates to influence the changes in the original odds of having neighborhood homicide. In other words, such a large magnitude of odds ratio might have confounded the actual impact of other predictors on the changes of the original odds of homicide in the neighborhoods. This study, therefore, determines to take the race/ethnic heterogeneity out for the 1993 logistic regression model. Then, it reruns the binary logistic regression, and reports new odds ratio scores below.

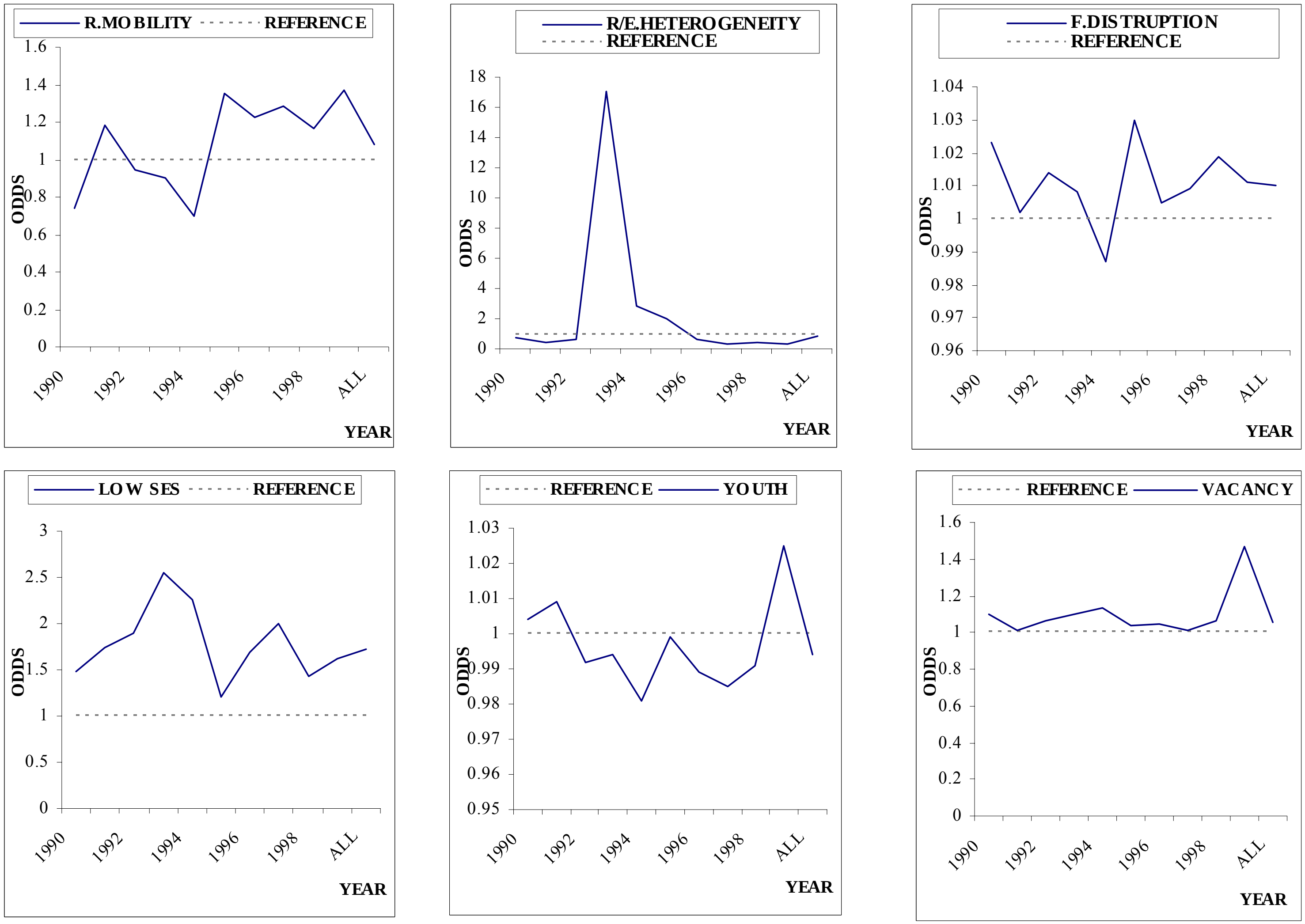
In terms of policy programs in the period between 1990 and 1999, Project Exile is not included into the models since it has uniform impact across the neighborhoods over the years. It would not be able to influence any changes in the odds of homicide across the neighborhoods. However, Blitz to Bloom is included in model 1999 and in the model established by a restructured data set covering all years. Since Blitz to Bloom was implemented in certain neighborhoods, its influential variation across the neighborhoods might be able to influence the changes in the odds of having neighborhood homicide.

Table 4.16: Binary Logistic Regression Models and Variables with Odds Ratios between 1990 and 1999 (See Appendix C)

YEAR	R.MOBILITY	R/E.HETEROGENEITY	F.DISTRUPTION	LOW SES	P.DENSITY	YOUTH	***VACANCY***
1990	.737	.694	**1.023***	**1.480***	1.000	**1.004***	**1.099***
1991	**1.183***	.380	**1.002***	**1.742***	1.000	**1.009***	**1.015***
1992	.946	.650	**1.014***	**1.902***	1.000	.992	**1.060***
1993	.903	**17.095***	**1.008***	**2.553***	1.000	.994	**1.103***
New 1993	**1.214***	N/A	**1.005***	**2.201***	1.000	.997	**1.008***
1994	.698	**2.838***	.987	**2.266***	1.000	.981	**1.134***
1995	**1.352***	**1.981***	**1.030***	**1.207***	1.000	.999	**1.033***
1996	**1.222***	.638	**1.005***	**1.684***	1.000	.989	**1.044***
1997	**1.289***	.314	**1.009***	**1.999***	1.000	.985	**1.015***
1998	**1.169***	.420	**1.019***	**1.426***	1.000	.991	**1.067***
1999	**1.371***	.308	**1.011***	**1.629***	1.000	**1.025***	**1.469***
ALL	**1.079***	.804	**1.010***	**1.728***	1.000	.994	**1.053***

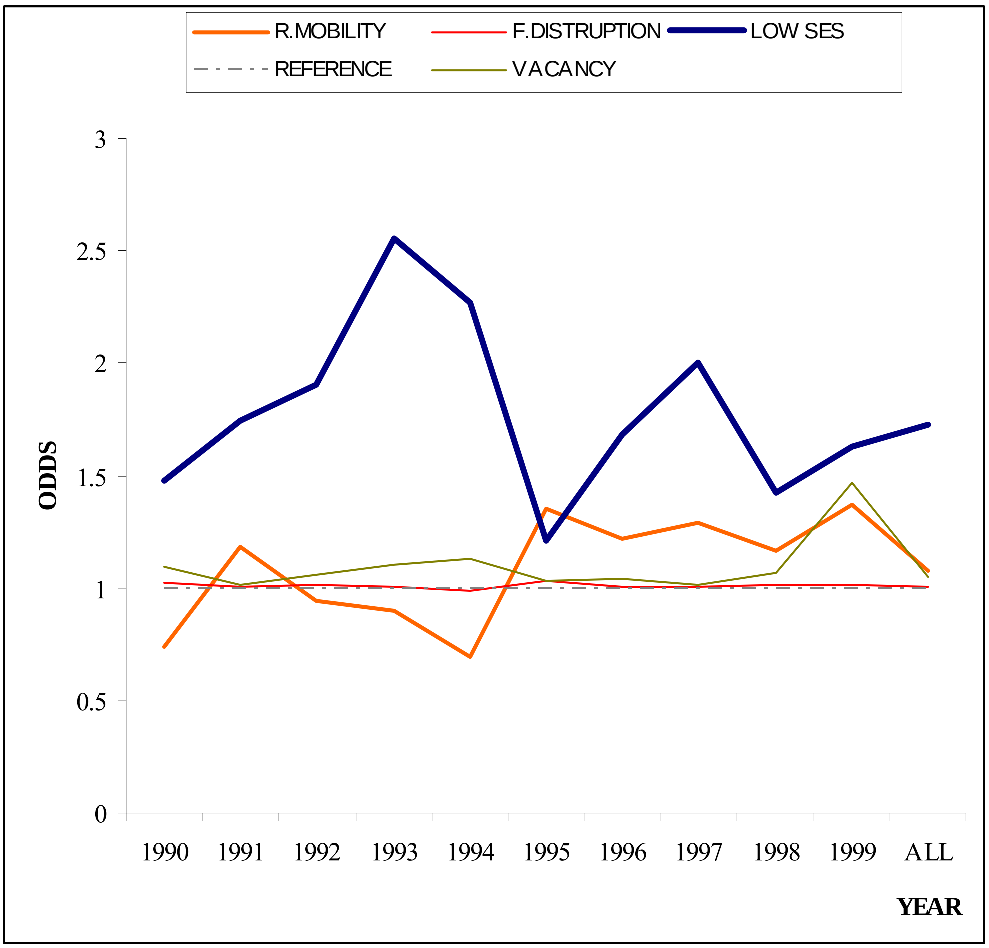
DV : Dummy homicide (0, 1) for each year. 0: No homicide in the neighborhood, 1: Yes homicide in the neighborhood.
ALL : 163 neighborhoods have been restructured for 10 years in SPSS, and obtained with 1630 cases.
* : Theoretically supported variables.
New 1993 : This model in 1993 was rerun after dropping race/ethnic heterogeneity since it had very large original odds, and overpowered the other variables' contributions in the model.

Figure 4.9: Odds ratios of Neighborhood Homicide with Reference = 1 (See Appendix C)



Once I realize the individual contribution of each predictor while all others are controlled in the binary logistic regression models, it is sensible to illustrate the odds ratios for the most influential variables together. Therefore, the reader can easily recognize their relative contribution to each other in the same plot (Figure 4.10) with the same scale.

Figure 4.10: The Most Important Predictors with Respect to Odds Ratios



According to the Figure 4.10, the most influential predictors should be recognized in following order: Low SES, Residential Mobility, Vacancy, and Family Disruption. The following context discusses whether these predictors (structural covariates) are consistent with Social Disorganization Theory as thoroughly interpreted for each year (Table 4.16; Figure 4.9; Figure 4.10). Here are the alternative hypotheses (except main hypothesis [H_8]) below to keep in the mind as the following context discusses the findings of the each model in each year.

H_1: As "residential mobility" increases so does the neighborhood homicide.

H_2: As "race/ethnic heterogeneity" increases so does neighborhood homicide.

H_3: As "family disruption" increases so does neighborhood homicide.

H_4: As "socio-economic status" decreases so does neighborhood homicide.

H_5: As "population density" increases so does neighborhood homicide.

H_6: As "youth population rate" increases so does neighborhood homicide.

H_7: As "vacancy rate" increases so does neighborhood homicide.

In 1990;

Family disruption, low SES, youth, and vacancy confirm the Social Disorganization Theory, whereas residential mobility, race/ethnic heterogeneity, and population density do not prove the theory. In fact, youth contributes little to influence the increases in the original odds of neighborhood homicide since its odds ratio has got only 1.004 ($p = .817$). In fact, one percentage increase in youth population increases only

.4% of the original odds of the neighborhood homicide as controlling for other variables in the model. Also, one percentage increase in family disruption increases 2.3% ($p = .024$) of the original odds of neighborhood homicide, whereas one percentage increase in vacancy rate increases almost 10% ($p = .006$) of the original odds of homicide in the neighborhoods as controlling for other variables in the model. Finally, low SES has the highest contribution (Odds ratio = 1.48; $p = .301$) such that one unit increase in the low SES factor increases the 48% of the original odds of homicide across the neighborhoods as controlling for other variables in the model. Interestingly, population density does not contribute anything to influence the changes in the original odds of neighborhood homicide. One reason would be that the City of Richmond is completely urbanized. And, the density of the neighborhoods across the city is almost the same although some neighborhoods are different than others (Figure 4.5).

In 1991;

Residential mobility, in this year, influences well for the increases in the odds of having homicide across the neighborhoods as opposed to the previous year. And it proves the Social Disorganization Theory. In fact, one unit increase in the residential mobility factor increases 18.3% ($p = .501$) of the original odds of neighborhood homicide as controlling for other variables in the model. On the other hand, family disruption (Odds ratio = 1.002; $p = .856$), youth (Odds ratio = 1.009; $p = .584$), and vacancy (Odds ratio = 1.015; $p = .631$) contribute very little (less than 2%) for the increases in the original odds of neighborhood homicide as controlling for other variables in the model. Of the most important predictors in the models, one unit increase in the low SES factor increases 74.2% (p = .109) of the original odds of having homicide in the neighborhoods as controlling for other variables in the model. In this year, race/ethnic heterogeneity index does not support the Social Disorganization Theory such that one unit *increase* in the race/ethnic heterogeneity index *decreases* 62% (p = .374) of the original odds of having neighborhood homicide as controlling for other variables in the model.

In 1992;

Residential mobility, as in 1990, does not support the theory such that one unit increase in the residential mobility factor *decreases* almost 5% (p = .836) of the original odds of neighborhood homicide as controlling for other variables in the model. Likewise, race/ethnic heterogeneity index (odds ratio = .650; p = .714), population density (odds ration = 1.000; p = .953), and youth (odds ratio = .992; p = .643) do not support the theory either. Family disruption, on the other hand, contributes little to increase the original odds of neighborhood homicide, and fairly confirms the theory. In fact, one percentage increase in the family disruption increases only 1.4% (p = .244) of the original odds of neighborhood homicide as controlling for other variables in the model. Vacancy rate influences the odds of having neighborhood homicide much more than family disruption does, and proves the theory as well. That is, one percentage increase in the vacancy rate increases 6% of the original odds of neighborhood homicide as controlling for other variables in the model. As the highest contributor, one unit increase in the low

SES factor increases 90.2% ($p = .104$) of the original odds of neighborhood homicide as controlling for other variables in the model 1992.

In 1993;

The study has initially included all independent variables as previously processed. However, this model has generated very large odds ratios (17.095) of race/ethnic heterogeneity for some underlying reasons in the City of Richmond. Then, it was taken out to avoid from its overpowering in the model such that it might have confounded the degree of other variables' contributions. With new model that does not include race/ethnic heterogeneity index in 1993; except youth predictor, all other variables consistently confirm the Social Disorganization Theory. In fact, one unit increase in the residential mobility factor increases 21.4% ($p = .429$) of the original odds of having neighborhood homicide as controlling for other variables in the model. One percentage increase in the family disruption increases only .5% ($p = .681$) of the original odds of having neighborhood homicide as controlling for other variables in the model. One unit increase in the low SES factor increases the original odds of having neighborhood homicide by a factor 2.2 ($p = .05$), when other variables are controlled in the model. One percentage increase in the vacancy rate increases almost 9% ($p = .016$) of the original odds of having neighborhood homicide, when other variables are controlled in the model. On the other hand, youth (odds ratio = .997; $p = .894$) influences almost nothing in the changes of the original odds of having the homicide. Again, population density does not influence anything in this model as previous models already recognized. Accordingly, it might be necessary to investigate this year and the next by constructing difference models later.

In 1994;

Residential mobility factor (odds ratio = .698; p = .285), family disruption (odds ratio = .987; p = .375), population density (odds ratio = 1.000; p = .041), and youth (odds ratio = .981; p = .436) do not confirm the theory, whereas racial/ethnic heterogeneity index (odds ratio = 2.838; p = .492), low SES factor (odds ratio = 2.266; p = .129), and vacancy (odds ratio = 1.134; p = .004) do prove the Social Disorganization Theory in 1994. Again, racial/ethnic heterogeneity index and low SES factor have got higher influences on increasing the original odds of neighborhood homicide as compared to other variables in the model. Speaking about the interpretation, one unit increase in the race/ethnic heterogeneity index increases the original odds of having neighborhood homicide by a factor 2.838, when other variables are controlled in the model. One unit increase in the low SES factor increases the original odds of having neighborhood homicide by a factor 2.266, when other variables are controlled in the model. Last, one percentage increase in the vacancy rate increases 13.4% of the original odds of having neighborhood homicide, when other variables are controlled in the model.

In 1995;

All social disorganization variables confirm the theory, except population density (odds ratio = 1.000; p = .531) and youth (odds ratio = .999; p = .938) in this year. Both population density and youth influences nothing in the changes of the original odds of having neighborhood homicide. On the other hand; one unit increase in the residential mobility factor increases 35.2% (p = .265) of the original odds of neighborhood homicide, when other variables are controlled in the model. One unit increase in the race/ethnic heterogeneity index increases the original odds of having neighborhood homicide by a factor 1.981, when other variables are controlled in the model. One percentage increase in the family disruption increases 3% (p = .047) of the original odds of having neighborhood homicide, when other variables are controlled in the model. One unit increase in the low SES factor increases 20.7% (p = .640) of the original odds of having neighborhood homicide, when other variables are controlled in the model. Last, one percentage increase in the vacancy rate increases 3% (p = .327) of the original odds of having neighborhood homicide, when other variables are controlled in the model.

In 1996;

Race/ethnic heterogeneity index (odds ratio = .638; p = .700), population density (odds ratio = 1.000; p = .145), and youth (odds ratio = .989; p = .519) predictors do not confirm the Social Disorganization Theory. That is, one unit increase in the race/ethnic heterogeneity index *decreases* almost 36% of the original odds of neighborhood homicide, when other variables are controlled in the model. Again, population density does not influence the original odds of neighborhood homicide. On the other hand, residential mobility, family disruption, low SES, and vacancy do prove the theory. In fact, one unit increase in the residential mobility increases 22.2% (p = .437) of the original odds of having neighborhood homicide, when other variables are controlled in the model. One percentage increase in the family disruption increases only .5% (p = .710) of the original odds of having neighborhood homicide, when other variables are controlled in the model. One unit increase in the low SES factor increases 68.4% (p = .165) of the original odds of having neighborhood homicide, when other variables are controlled in the model. One percentage increase in the vacancy rate increases 4.4% (p = .167) of the original odds of having neighborhood homicide, when other variables are controlled in the model.

In 1997;

The Project Exile was initiated in this year. Unfortunately, it is not possible to declare any dummy variable for the Project Exile since it has uniform effect across the neighborhoods. Again, seven (7) structural covariates and the neighborhood homicide (as a dummy variable) are the essential variables to construct a binary logistic regression in 1997. In this year, race/ethnic heterogeneity index (odds ratio = .314; p = .303), population density (odds ratio = 1.000; p = .580), and youth (odds ratio = .985; p = .397) predictors do not confirm the Social Disorganization Theory. That is, one unit increase in the race/ethnic heterogeneity index *decreases* almost 69% of the original odds of neighborhood homicide, when other variables are controlled in the model. One percentage increase in the youth rate decreases only 2% of the original odds of neighborhood homicide as other variables are controlled in the model. On the other hand, residential mobility factor, family disruption, low SES factor, and vacancy do confirm the theory. In fact, one unit increase in the residential mobility increases 28.9% of the original odds ($p = .309$) of having neighborhood homicide, when other variables are controlled in the model. One percentage increase in the family disruption increases only .9% ($p = .551$) of the original odds of having neighborhood homicide, when other variables are controlled. One unit increase in the low SES factor increases 99.9% of the original odds of having neighborhood homicide, when other variables are controlled in the model. One percentage increase in the vacancy rate increases 1.5% ($p = .628$) of the original odds of having neighborhood homicide, when other variables are controlled in the model.

In 1998;

Race/ethnic heterogeneity index (odds ratio = .420; $p = .459$), population density (odds ratio = 1.000; $p = .903$), and youth (odds ratio = .991; $p = .616$) predictors do not confirm the Social Disorganization Theory. That is, one unit increase in the race/ethnic heterogeneity index *decreases* 58% of the original odds of neighborhood homicide as other variables are controlled in the model. One percentage increase in the youth rate decreases only 1% of the original odds of neighborhood homicide, when other variables are controlled in the model. Population density, again, does not influence the odds of neighborhood homicide. On the other hand, residential mobility factor, family disruption, low SES factor, and vacancy do confirm the theory. In fact, one unit increase in the residential mobility increases 16.9% ($p = .549$) of the original odds of having neighborhood homicide, when other variables are controlled. One percentage increase in the family disruption increases almost 2% (p = .262) of the original odds of having neighborhood homicide, when other variables are controlled. One unit increase in the low SES factor increases 42.6% (p = .301) of the original odds of having neighborhood homicide, when other variables are controlled. One percentage increases in the vacancy rate increases 6.7% (p = .029) of the original odds of having neighborhood homicide, when other variables are controlled in the model.

In 1999;

Race/ethnic heterogeneity index (odds ratio = .308; p = .315), population density (odds ratio = 1.000; p = .683), and youth (odds ratio = .986; p = .500) predictors do not confirm the Social Disorganization Theory. That is, one unit increase in the race/ethnic heterogeneity decreases almost 69% of the original odds of neighborhood homicide, when other variables are controlled in the model. One percentage increase in the youth *decreases* almost 2% of the original odds of neighborhood homicide as controlling other variables in the model. Population density does not influence the odds of neighborhood homicide. On the other hand, residential mobility factor (odds ratio = 1.371; p = .232), family disruption (odds ratio = 1.011; p = .539), low SES factor (odds ratio = 1.629; p = .125), and vacancy (odds ratio = 1.025; p = .456) do confirm the theory. In fact, one unit increase in the residential mobility factor increases 37.1% of the original odds of having neighborhood homicide, when other variables are controlled. One percentage increase in the family disruption increases 1.1% of the original odds of having neighborhood homicide, when other variables are controlled. One unit increase in the low SES factor increases 62.9% of the original odds of having neighborhood homicide, when other variables are controlled. One percentage increase in the vacancy increases 2.5% of the original odds of having neighborhood homicide, when other variables are controlled. The blitz to bloom variable in 1999 provides interesting result such that being a neighborhood that Blitz-to-Bloom program was implemented increases 46.9% of the original odds of neighborhood homicides, when other variables are controlled in the model. Consequently, this study has not been able to realize the influence of Blitz to Bloom program on *reducing* odds ratios of neighborhood homicide over the year although Smith (2001) did reveal its short term impact on crime reduction for the neighborhoods in the Bloom.

In ALL;

This study restructured the data set, and established 1630 (163 [number of neighborhoods]*10 [number of years] = 1630) cases. It, therefore, attempts to comprehend the contribution of each structural covariate on influencing the original odds of having homicide across the neighborhoods in the study period of time (From 1990 to 1999). In this model, residential mobility factor (odds ratio = 1.079; p = .346), family disruption (odds ratio = 1.010; p = .006), low SES factor (odds ratio = 1.728; p = .000), and vacancy (odds ratio = 1.053; p = .000) do confirm the theory, whereas racial/ethnic heterogeneity index (odds ratio = .804; p = .554), population density (odds ratio = 1.000; p = .164), and youth (odds ratio = .994; p = .289) do not support the theory. Speaking about the inconsistency with Social Disorganization Theory, racial/ethnic heterogeneity and youth negatively influences the original odds of homicide across the neighborhoods in this model. In fact, one unit increase in the race/ethnic heterogeneity index *decreases* almost 20% of the original odds of neighborhood homicide, when other variables are controlled in the model. One percentage increase in the youth decreases almost 1% of the original odds of neighborhood homicide as controlling the other variables in the model. Again, population density does not influence the odds of neighborhood homicide in this model. On the other hand, one unit increase in the residential mobility factor increases almost 8% of the original odds of having neighborhood homicide, when other variables are controlled. One percentage increase in the family disruption increases 1.0% of the original odds of having neighborhood homicide, when other variables are controlled. One unit increase in the low SES factor increases almost 73% of the original odds of having neighborhood homicide, when other variables are controlled. One percentage increase in the vacancy increases 5.3% of the original odds of having neighborhood homicide, when other variables are controlled. Blitz to Bloom, as a dummy variable, in this model does negatively influence the original odds of having neighborhood homicide. That is, being a neighborhood that Blitz-to-Bloom program was implemented in 1999 decreases almost 8% of the original odds of having neighborhood homicide as compared to other neighborhoods without the program, when other variables are controlled in the model. As opposed to the model in 1999, this model reveals the influence of this program on decreasing the odds of having neighborhood homicide over the 10 years. This model, therefore, allows the research to compare the influence of Blitz-to-Bloom over the years and across the neighborhoods. In comparing the other years to 1999, the Blitz-to-Bloom successfully decreased the odds of having neighborhood homicide while statistically controlling other structural variables in this model.

Note that, significance levels of measurements are not relevant in this study. Rather, this study focuses on how much each independent variable influences the changes of the original odds of homicide, when other variables are controlled. Accordingly, each hypothesis has only been assessed with respect to the odds ratios (e^B) for each year from 1990 to 1999 and all years although their significance levels are also provided for the readers.

Taken together, *low SES factor*, *vacancy*, and *family disruption* all consistently support Social Disorganization theory over the years. Population density does not support the theory at all since the City of Richmond has almost similar degree of population density across the neighborhoods from 1990 to 1999. Although population density might be important structural covariate in SDT to change the odds of neighborhood homicide, examining all neighborhoods might have attenuated the influence of population density on changing the original odds of the homicide. Surprisingly, racial/ethnic heterogeneity does not prove the theory, except the years 1993, 1994, and 1995. Presumably, majority of the neighborhoods have already diverse racial/ethnic groups across the city, and such invariance in the heterogeneity index across the neighborhoods might not become enough to influence the original odds of neighborhood homicide, when other variables are controlled in the model. In other words, diverse communities in the City of Richmond might have got used to live together with different racial/ethnic groups in their neighborhoods. This finding makes the City of Richmond unique to inspect such unusual finding against the Social Disorganization Theory. On the contrary, these results address the influence of isolated groups on experiencing more neighborhood homicide, and confirm Wilson's (1987) approach in that isolated social groups with higher poverty should be considered socially disadvantaged across the neighborhoods.

The following section further examines these years in which racial/ethnic heterogeneity does confirm the theory. Residential mobility, on the other hand, does support the Social Disorganization Theory, except the years 1990, 1992, 1993, and 1994. In all other years, residential mobility shows reverse direction as influencing the changes the original odds of homicide in the neighborhoods. Meaning that, one unit increase in the residential mobility factor *decreases* the odds of neighborhood homicide when the other variables are controlled in the model. Consequently, these years are appealing this study to further investigating with the following difference models by Multinomial Logistic Regression.

Multinomial Logistic Regression (MLR) Analysis

Multinomial Logistic Regression is utilized to predict the probability of each class within dependent variable (having 3 or more classes within) in terms of a set of predictors (IVs) (Garson, 2007). IVs might be continuous, discrete, or just mix of them. The IVs, in other words, might be either factors and/or covariates. The ultimate goal is, therefore, to classify the categories of outcome variable based on various types of independent variables. From this perspective, multinomial logistic regression might be considered similar to *binomial logistic regression*, whereas multinomial regression is not just restricted to DVs with only two categories. The basic assumption is that odds ratio of *any two* categories be independent of all categories within DV. Covariates should also be independent to each other in MLR model.

In this study, dependent variable has three different categories such as “decrease”, “no change”, and “increase”. To logically test the main hypothesis (Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time), this study declares the “no change” as a reference category, and interprets “increase” and “decrease” with respect to “no change” category.

As an analytical strategy, this study utilizes the subsequent ranges to construct difference models as it reveals whether the change in neighborhood homicide rates might be explained by the change in neighborhood social disorganization over the years. Once homicide trends in the city are carefully examined in Figure 4.8, 9 (nine) difference models are constructed by the following ranges 1990-1999, 1990-1994, 1994-1999, 1993-1994, 1994-1995, 1996-1997, 1997-1998, 1998-1999, and 1997-1999. As discussed before, neighborhoods in a city may not change their common characteristics in a very short time, but it takes some time to observe any major changes in neighborhoods. However, this study might miss the peak decreases and increases if it only treats with 10 (ten) year or 5 (five) year ranges. Instead, it rationally approaches to determine such appropriate ranges to explore the change in neighborhood homicide rates associated with the change in neighborhood social disorganization over time.

Sensibly, this study investigates the difference models by these ranges while it expects to see actual changes in neighborhood homicide and social disorganization over the years.

In MLR, each explanatory variable comprises (k-1) number of logits, in which k should be considered as the number categories in DV (Garson, 2007). In constructing Multinomial Logistic Regression, once dependent variable is selected, the researcher is supposed to declare the reference category among k number of categories. This choice heavily depends on the researcher's preference. For the sake simplicity and reasonable interpretation, this study prefers "no change" category to declare as a reference one. Then, it assesses other groups' (Increase or decrease) differences with respect to "no change" in MLR. This study has only one factor such as Blitz-to-Bloom. Factors are usually categorical variables in MLR although some might be numerical. On the other hand, all other independent variables are included as covariates in MLR. Since this study only tests the main social disorganization indicators, it only deals with main effects of these variables in MLR.

Speaking about specific statistics in MLR, iterative maximum-likelihood (MLE) algorithm is used to perform parameter estimation in multinomial logistic regression (Garson, 2007). Similar to logistic regression, MLR uses the following statistics to model the probabilities of changes within DV: -2 log-likelihood, Pearson and deviance Chi-Square goodness of fit, Cox and Snell, Nagelkerke, and McFadden R^2. However; of the most common preference, this study only takes Nagelkerke R^2 into consideration in the following table. The actual SPSS outputs are placed within Appendix D.

As in the binary logistics regression, significance levels are not relevant in MLR either since this study works with entire population. This study, therefore, determines whether its main hypothesis is supported by the findings or not with respect the magnitude and direction of the odds changes having neighborhood homicide increase for each time interval.

Table 4.17: Difference Models with Multinomial Logistic Regression (See Appendix D)

RANGES*	GOODNESS -OF-FIT (Pearson)	NAGELKERGE R^2	*Likelihood Ratio Tests (Model Fitting Information)*		
			Chi-Square	df	Sig.
1990-99	**.214**	**.241**	**37.396**	**18**	**.005**
1990-94	**.378**	**.199**	**30.760**	**14**	**.031**
1994-99	**.265**	**.191**	**29.416**	**18**	**.021**
R.1993-94	**.362**	**.210**	**32.768**	**12**	**.001**
1994-95	**.381**	**.148**	**22.392**	**14**	**.071**
R.1996-97	.298	.078	11.249	12	.508
R.1997-98	.251	.072	10.524	12	.570
R.1998-99	**.297**	**.178**	**26.879**	**16**	**.043**
1997-99	**.273**	**.223**	**34.145**	**18**	**.012**

* : These ranges are determined based on the homicide trend analysis (Figure 4.1).
DV (Three cat.) : 1 = No change, 2= Decrease, and 3= Increase.
R : If the model is rerun after dropping the inflated odds ratios in the initial model.

Table 4.17, a composite table covering all MLR models for all convenient ranges (based upon the trend analysis of homicide rate, Figure 4.8), clearly determines the Goodness-of-Fit, Nagelkerke R-square, Chi-Square, number of degrees of freedom (dfs), and significance level of the likelihood ratio tests. While MLR is used to assess model-building, this study uses the chi-square value to assess model fit. Note that, some models have acceptable Goodness-of-Fit ($p \geq .05$) scores, and result in well-fitting models although some of them include terms that are not shown to be significant using a

Multinomial Logistic Regression. If the logistic regression models were not significant, that would indicate that the term(s) in the full model, but not in the reduced model did not add significantly to the model, even though the overall model fit was well-fit. In fact, that is normal, and sensible to accept in constructing MLR. Since significance level is not actually relevant in this study, we just disregard the significance level scores in the Table 4.18. Taken together: Although all (nine) models are only well-fit, seven of nine difference models are both well-fit ($p \geq .05$) and significant ($p \leq .05$). The following context discusses the contribution of each difference variable, and investigates whether findings in the Table 4.18 support the main hypothesis of this study. To remind, the main hypothesis of this dissertation is:

> *H_8: Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time.*

Changes in neighborhood social disorganization are determined by differencing the individual scores of seven structural covariates (as used in LR models) in each time step of the ranges, such as residential mobility, race/ethnic heterogeneity, family disruption, low SES, population density, youth, and vacancy. Homicide will be used as a neighborhood crime while this study interprets the results of the difference models. Table 4.18 allows the research thoroughly discuss the findings with respect to the time intervals. The breakdowns for the ranges have already been determined by the homicide trend plot (Figure 4.8). In fact, this study starts examining the change processes by the

1990 – 1999, 10 year difference; this would provide the research with overall perspective without accounting the individual yearly changes in City of Richmond. Nonetheless, only this range would not be enough to determine whether change in neighborhood homicide is likely to be associated with the change in neighborhood social disorganization over the years.

The difference model between 1990 and 1999;

Change in residential mobility factor (odds ratio = 2.683; p = .05), change in race/ethnic heterogeneity index (odds ratio = 1.022; p = .99), change in Family disruption (odds ratio = 1.020; p = .15), and change in low SES factor (odds ratio = 1.072; p = .847) confirm the main hypothesis above, whereas, change in population density (odds ratio = 1.000; p = .853), change in youth (odds ratio = .950; p = .182), and change in vacancy (odds ratio = .992; p = .85) do not prove the hypothesis. Each one unit *increase* in the residential mobility change from 1990 to 1999 increases the original odds of neighborhood homicide *increase* by the factor 2.683 as compared to "no change" category, when controlling for other change variables in the model. Each one unit *increase* in the race/ethnic heterogeneity change from 1990 to 1999 increases the original odds of neighborhood homicide *increase* by about 2.2% as compared to "no change" category, when controlling for other change variables in the model. Each one percentage *increase* in the family disruption change from 1990 to 1999 increases the original odds of neighborhood homicide *increase* by about 2.0% as compared to "no change" category, when controlling for other change variables in the model. Each one unit *increase* in the low SES change from 1990 to 1999 increases the original odds of neighborhood homicide *increase* by 7.2% as compared to “no change” category, when controlling for other change variables in the model. Being neighborhoods treated by Blitz to Bloom increases the original odds of neighborhood homicide *increase* by a factor 3.641 (p = .072) as compared to “no change” category, when controlling for other change variables in the model.

The difference model between 1990 and 1994;

Change in youth (odds ratio = 1.048; p = .489) and change in vacancy (odds ratio = 1.137; p = .123) confirm the main hypothesis above, whereas, Change in residential mobility (odds ratio = .859; p = .795), change in race/ethnic heterogeneity (odds ratio =.322; p = .802), change in Family disruption (odds ratio = .964; p = .086), and change in low SES (odds ratio = .888; p = .853), change in population density (odds ratio = 1.000; p = .156) do not. Each one percentage *increase* in the youth change from 1990 to 1994 increases the original odds of neighborhood homicide *increase* by about 4.8% as compared to “no change”, when controlling for other change variables in the model. Each one unit *increase* in the vacancy change from 1990 to 1994 increases the odds of neighborhood homicide *increase* by about 13.7% as compared to “no change”, when controlling for other change variables in the model.

Table 4.18: Multinomial Logistic Regression Models and Change Variables with their Odds Ratios (See Appendix D)

RANGE	CHANGE IN R.MOBILITY	CHANGE IN R/E.HETEROGENEITY	CHANGE IN F.DISTRUPTION	CHANGE IN LOW SES	CHANGE IN P.DENSITY	CHANGE IN YOUTH	***CHANGE IN VACANCY***
1990-99	**2.683***	**1.022***	**1.020***	**1.072***	1.000	.950	.992
1990-94	.859	.322	.964	.888	1.000	**1.048***	**1.137***
1994-99	**4.746***	**4.064***	**1.038***	**1.375***	1.000	.909	**1.055***
R.1993-94	.004	N/A	.900	.091	.994	**1.496***	**1.890***
1994-95	.028	4.69E-014	.901	**11.429***	1.003	**1.117***	**2.755***
R.1996-97	**4.941***	N/A	.920	**13.025***	.998	**1.340***	.996
R.1997-98	N/A	**2.656***	.941	.292	.998	**1.161***	.925
R.1998-99	**N/A**	.720	.994	**10.564***	.999	.947	**1.046***
1997-99	**10.239***	.059	.977	**8.753***	1.000	.837	.961

DV : Categorical homicide (1, 2, and 3) for each range, such as 1: "No change", 2: "Decrease" and 3: "Increase"
Reference : 1 "No change". Odds ratios are, with respect to the reference, reported for the only "increase" category within the categorical homicide change over time.
R : If the model were rerun after dropping the inflated odds ratios in the initial model
*** : Confirming the main hypothesis.**

The difference model between 1994 and 1999;

The difference model has performed well in this range such that contribution of each change variable confirms the main hypothesis, except only population density and youth. Clearly, population density has not got any explanatory power in either LR or MLR models so far. In fact, Each one unit *increase* in the residential mobility change from 1994 to 1999 increases the odds of neighborhood homicide *increase* by the factor 4.746 (p = .064) as compared to “no change in homicide”, when controlling for other change variables in the model. Each one unit *increase* in the race/ethnic heterogeneity change from 1994 to 1999 increases the odds of neighborhood homicide *increase* by the factor 4.044 (p = .765) as compared to “no change”, when controlling for other change variables in the model. Each one unit *increase* in the family disruption change from 1994 to 1999 increases about 4% (p = .122) of the original odds of neighborhood homicide *increase* as compared to “no change” category, when controlling for other change variables in the model. Each one unit *increase* in the low SES change from 1994 to 1999 increases about 38% (p = .656) of the original odds of neighborhood homicide *increase* as compared to “no change” change category, when controlling for other change variables in the model. Each one unit *increase* in the vacancy change from 1994 to 1999 increases about 6% (p = .492) of the original odds of neighborhood homicide *increase* as compared to “no change” category, when controlling for other change variables in the model. Being neighborhoods treated by Blitz to Bloom increases the original odds of exposing neighborhood homicide *increase* by a factor 7.740 (p = .008) as compared to “no change” category, when controlling for other change variables in the model.

The difference model between 1993 and 1994;

The MLR has been run two times for this range. This study initially realized large odds ratio for race/ethnic heterogeneity change that might have confounded other change variables' contributions on influencing the odds of having homicide increase across the neighborhoods. To avoid from overpowering, this study has just dropped this variable, and rerun the MLR difference model for the range between 1993 and 1994. According the final model shown in both Table 4.19 and Table 4.20, change in youth (odds ratio = 1.496; p = .148) and change in vacancy (odds ratio = 1.890; p = .06) confirm the main hypothesis, whereas change in residential mobility (odds ratio = .004; p = .104), change in family disruption (odds ratio = .900; p = .186), change in low SES (odds ratio = .091; p = .386), and change in population density (odds ratio = .994; p = .007) do not prove the main hypothesis. In fact, each one unit *increase* in the youth change from 1993 to 1994 increases about 50% of the original odds of homicide *increase* as compared to "no change" category, when controlling for other change variables in the model. Each one unit *increase* in the vacancy change from 1993 to 1994 increases about 89% of the original odds of homicide *increase* as compared to "no change", when controlling for other change variables in the model.

The difference model between 1994 and 1995;

Change in low SES factor (odds ratio = 11.429; p = .442), change in youth (odds ratio = 1.117; p = .701), and change in vacancy (odds ratio = 2.755; p = .012) prove the main hypothesis, whereas al others do not confirm the hypothesis in this range. In fact, each one unit *increase* in the low SES change from 1994 to 1995 increases the original odds of homicide *increase* by the factor 11.429 as compared to "no change" category, when controlling for other change variables in the model. Each one unit *increase* in the youth change from 1994 to 1995 increases the original odds of homicide *increase* by the factor 2.755 as compared to "no change" category, when controlling for other change variables in the model.

The difference model between 1996 and 1997;

The MLR has been run two times for this range as well. This study initially realized large odds ratio for race/ethnic heterogeneity change that might have confounded other change variables' contributions on influencing the original odds of having neighborhood homicide increase across the neighborhoods. To avoid from overpowering, this study has just dropped this variable, and rerun the MLR difference model for the range between 1996 and 1997. Accordingly, change in residential mobility (odds ratio = 4.941; p = .584), change in low SES (odds ratio = 13.025; p = .322), and change in youth (odds ratio = 1.340; p = .279) confirm the main hypothesis, whereas all others do not. In fact, each one unit *increase* in the residential mobility change from 1996 to 1997 increases the original odds of neighborhood homicide *increase* by the factor 4.941 as compared to "no change" category, when controlling for other change variables in the model. Each one unit *increase* in the low SES change from 1996 to 1997 increases the original odds of neighborhood homicide *increase* by the factor 13.025 as compared to "no change" category, when controlling for other change variables in the model. Each one unit *increase* in the youth change from 1996 to 1997 increases 34% of the original odds of neighborhood homicide *increase* as compared to “no change” category, when controlling for other change variables in the model.

The difference model between 1997 and 1998;

The MLR has been run two times for this range as well. This study initially realized large odds ratio for residential mobility change that might have confounded other change variables’ contributions on influencing the original odds of having neighborhood homicide increase. To avoid from overpowering, this study has just dropped this variable, and rerun the MLR difference model for the range between 1997 and 1998. In the last version of the model, race/ethnic heterogeneity change (odds ratio = 2.656; p = .956) and youth change (odds ratio = 1.161; p = .564) confirm the main hypothesis, whereas all others do not. That is, each one unit *increase* in the race/ethnic heterogeneity change from 1997 to 1998 increases the original odds of neighborhood homicide *increase* by the factor 2.656 as compared to “no change” category, when controlling for other change variables in the model. Each one unit *increase* in the youth change from 1997 to 1998 increases about 16% of the original odds of neighborhood homicide *increase* as compared to “no change” category, when controlling for other change variables in the model.

The difference model between 1998 and 1999;

The MLR has been run two times for this range as well. This study initially realized very large odds ratio for residential mobility change that might have confounded other change variables' contributions on influencing the original odds of having neighborhood homicide increase. To avoid from overpowering, this study has just dropped this variable, and rerun the MLR difference model for the range between 1998 and 1999. Ultimately, change in low SES (odds ratio = 10.564; p = .381) and change in vacancy (odds ratio = 1.046; p = .864) confirm the main hypothesis, whereas all others do not. In other words, each one unit *increase* in the low SES change from 1998 to 1999 increases the original odds of neighborhood homicide *increase* by the factor 10.564 as compared to "no change" category, when controlling for other change variables in the model. Each one unit *increase* in the vacancy change from 1998 to 1999 increases the original odds of neighborhood homicide *increase* by about 5% as compared to "no change" category, when controlling for other change variables in the model. Being neighborhoods treated by Blitz to Bloom increases the original odds of exposing neighborhood homicide *increase* by a factor 14.530 (p = .002) as compared to "no change" category, when controlling for other change variables in the model. Consequently, Blitz to Bloom program has no explanatory power over the year to reduce the odds of neighborhood homicide *increase*. That is, difference model between 1998 and 1999 recognizes that neighborhoods in the Bloom themselves result in higher odds of homicide by the factor 14.530.

The difference model between 1997 and 1999;

Change in residential mobility (odds ratio = 10.239; p = .198) and change in low SES (odds ratio = 8.753; p = .166) confirm the main hypothesis, whereas all other change variables do not confirm the hypothesis in this difference model between 1997 and 1999. In other words, each one unit *increase* in the residential mobility change from 1997 to 1999 increases the original odds of neighborhood homicide *increase* by the factor 10.239 as compared to "no change" category, when controlling for other change variables in the model. Each one unit *increase* in the low SES change from 1997 to 1999 increases the original odds of neighborhood homicide *increase* by the factor 8.753 as compared to "no change" category, when controlling for other change variables in the model. Being neighborhoods treated by Blitz to Bloom increases the original odds ratios of exposing homicide "increase" by a factor 11.610 (p = .004) as compared to "no change" category, when controlling for other change variables in the model.

Hotspot Analysis of Homicides Incidents

This section assesses the homicide hotspots with respect to both incidents based distribution and aggregated homicide rates into the neighborhoods. This study utilizes spatial analysis extension of ArcGIS 9.1 to recognize the homicide incidents hotspots (Figure 4.9) regardless of the neighborhood boundary. This approach is based on the pin-mappings. As a second approach to realize and statistically confirm the hotspots, this section computes Moran's I statistics, and therefore, realizes whether homicide rates are spatially dependent to certain neighborhoods in separate years.

Interestingly enough, most police departments only deal with pin mappings, as descriptive maps, for crime analysis in their territories. For the policy consideration and further reliable research findings, however; this study needs to construct much more analytical maps such as crime hotspot analysis and thematic maps in relation to structural covariates across the neighborhoods. On the other hand, one should really understand why researchers might prefer different mapping styles for the purpose of their analyses. Different maps and styles might actually specify the differences between pin-mappings and thematic maps across the neighborhoods.

Pin mappings and thematic mappings might have different purposes. Police would like to see specific addresses of crime incidents, and focuses on these specific addresses in their daily duties. Rather than thinking in the long term, they mostly concentrate on today's emerging problems with their territories. Nonetheless, the pin maps might also be utilized to construct the hotspots of incident distribution, and further examine the movements of such clusters over the years. More specifically, by video animation including all years, hotspot distribution might perfectly allow the researchers to determine which neighborhoods are more vulnerable for the crime hotspots, and in which directions they move over the years. Further, they can realize repeatedly victimized neighborhoods by the crime hotspots over the years.

According to Figure 4.11, homicide hotspots have been generally recognized in certain neighborhoods located north-east and/or east side of the city although they slightly move from one neighborhood to another over the years. In figure 4.11, this study did not prefer to place the labels of neighborhoods' names on the homicide hotspots so as to noticeably visualize them in a plain environment. Otherwise, such many included elements of the maps would be an obstacle to convey the essential message to the readers. At the end of hotspot analysis, this section includes a descriptive map for where the neighborhoods in the City of Richmond are distributed, and one can easily compares the homicide hotspots fallen to the neighborhood(s).

Taken together, the following context reveals the names of the neighborhoods that experienced homicide hotspot(s) in each year from 1990 to 1999.

In 1990, *Blackwell, Gilpin*, the intersection of *Mosby, Brauers, and Fairmont* neighborhoods all has the densest hotspots. The intersections of the *Fan, Randolph, and Byrd Park* have fewer degrees of homicide hotspots than previous neighborhoods in northeast and/or east side of the city. On the other hand, some neighborhoods in the southwest side of the city had also one homicide hotspot in 1990. For instance, neighborhood Beaufond had a detectable hotspot although its intensity was less than the ones experienced in the northeastern of the city.

In 1991, Gilpin neighborhood keeps exposing more homicide hotspot than previous year. In fact, the hotspots in the intersection *Mosby, Brauers, and Fairmont neighborhoods* just moved into Gilpin Neighborhood. In such hotspot movements, *Whitcomb* neighborhood contiguous to this intersection has pulled the most of hotspots previously experienced. The diffusion of previous years' hotspots is clearly realized in 1991. *Blackwell* still experienced some homicide hotspot although some portion of hotspot diffused into the contiguous neighborhoods through the south such as the intersection of *Oak Grove* and *Hillside Court* neighborhoods. Interestingly, *Windsor* neighborhood had firstly experience homicide hotspot although there was no homicide hotspot in 1990. Although *Beaufond* had experienced homicide incidents in 1991, they don't seem clustering in 1991. It would be confident to say that homicide hotspots are experienced in certain neighborhoods geographically close to each so far.

In 1992, again; *Blackwell* and *Windsor* neighborhoods keep exposing homicide hotspots as well as Windsor neighborhood does. Interestingly, the hotspots in *Gilpin* and *Whitcomb* neighborhoods disappeared, and the larger hotspots being appeared together in the area including more neighborhoods contiguous to each, such as *Mosby*, *Brauers, Fairmont, Woodville,* and *Fairfield* neighborhood. These are located in almost one mile circular area in the northeastern of the city. Beaufond neighborhood, on the other hand, had denser hotspot in 1992. The hotspot in here was especially observed on the edge (boundary) between *Beaufond* and Midlothian neighborhood. Still, the hotspots keep appearing in the same neighborhoods or very close to them.

In 1993, the edge of *Beaufond* and Midlothian neighborhood was still problematic with respect to homicide hotspot. Again, *Blackwell* and *Windsor* neighborhoods still expose homicide hotspots in 1993. *Mosby* and *Fairmont* neighborhoods, contiguous to each, experience homicide hotspots. The boundary edge between *Windsor* and *Bellemeade* neighborhoods represents homicide hotspot as well. In 1993, the intersection of *Fan* and *Randolph* seems problematic with respect to have homicide hotspot.

In 1994, *Blackwell* and *Windsor* neighborhoods keep exposing homicide hotspots. Close to them, the intersection of *Hillside Court, Oak Gove,* and *Bellemeade* neighborhoods experience homicide hotspot in this year although this place did not experience any cluster in 1993. The intersection of *Fan* and *Randolph* neighborhoods keep experiencing homicide hotspots in this year. Northeastern part (Whitcomb, Brauers, and Fairmount neighborhoods) of the city has still experienced homicide hotspots, but they seem less severe as opposed to previous years.

In 1995, *Whitcomb* and *Mosby* neighborhoods keep having denser homicide hotspots. *Jackson Ward* and *Monroe Ward* together expose hotspots although they did not experience in previous year. *Old Town Manchester* contiguous to Blackwell has got homicide hotspot. This neighborhood experienced a spillover effect such that the homicide hotspots just moved from Blackwell to Old Town Manchester neighborhood. It is confident to say that hotspots do not go far away from one year to next, but they keep moving around the contiguous neighborhoods over time. Again, *Windsor* neighborhood keeps having hotspots in 1995. Beaufond neighborhood still exposes homicide hotspot in some degree.

In 1996, Beaufond neighborhood did not experience homicide hotspot, whereas Blackwell, Windsor, Fairmount, and Union Hill neighborhoods keep exposing hotspots. As a first, *Creighton* neighborhood unusually has got homicide hotspots in this year. However, this neighborhood is very close to the most problematic neighborhoods with respect to homicide and higher level neighborhood social disorganization as clearly seen in previous descriptive thematic and hotspot maps.

In 1997, the City of Richmond has experienced the most intensive homicide hotspots across the neighborhoods. *Carytown* neighborhood at the corner of *West of the Boulevard* and the *Fan* has firstly experienced homicide hotspots in 1997. The area including Mosby, Fairmont, Church Hill North, Woodville and Creighton together expose a large homicide hotspot in northern part of the city. Another large hotspot is realized in the area covering Gilpin, Southern Barton Heights, and Highland Park Southern Tip neighborhoods in 1997. Interestingly, Southern Barton Heights and Highland Park Southern Tip have firstly been influenced by homicide hotspots. Similarly, Fulton neighborhood just located at the east of the city has firstly exposed homicide hotspot in 1997. Blackwell neighborhood, again, has got homicide hotspot in some degree.

In 1998, interestingly enough, very dense homicide hotspots in 1997 disappeared and/or turned into only one small hotspot after just Project Exile. Such unique homicide hotspot in this year was located in *Highland Park Southern Tip neighborhood*. It is interesting that this neighborhood was insistently exposed by the homicide hotspots although all other hotspots across the city have been partially or completely disappeared after the Project Exile. Other neighborhoods that, some what had experienced homicide hotspots so far have still experienced few incidents, but they did not turn into hotspot in this year. Therefore, the city had much more plain environment with respect to homicide distribution except very severe hotspot located in Highland Park Southern Tip neighborhood.

In 1999, however; homicide hotspots turned back to previous pattern in 1999 although the homicide rates kept decreasing after 1997. Of the most well known, the area covering Mosby, Fairmont, and Union Hill has got back very large homicide hotspot. North side of the Highland Park Southern Tip and Green Park neighborhoods generated a new homicide hotspot in this year. The intersection of Virginia Union, and Northern Barton Heights neighborhoods experienced homicide hotspot in this year. Accordingly, new neighborhoods have got homicide hotspots such that they have never experienced homicide hotspots in previous years.

Taken together, only certain numbers of neighborhoods in the City of Richmond have exposed homicide hotspots from 1990 to 1999. Some of them were repeatedly victimized by the homicide hotspots, whereas some of them only one or two times experienced homicide hotspot(s) over the years. Among them, Old Town Manchester, Monroe Ward, and Carytown neighborhoods are business centers, whereas all other neighborhoods having homicide hotspots are residential neighborhoods in the city.

Table 4.19 puts these repeatedly victimized neighborhoods together for each year, therefore; one can easily reveal the most problematic neighborhoods with respect to the homicide hotspots from 1990 to 1999. Only 29 neighborhoods out of 163 were victimized by the homicide hotspots in this time interval. These limited numbers of neighborhoods having homicides, and the others having no homicides across the neighborhoods have become one of the main justifications why this study performed logistic regression and its versions for its multivariate statistical analyses.

Table 4.19: Neighborhoods Exposing Homicide Hotspot(s) form 1990 to 1999

Neighborhoods	***1990***	***1991***	***1992***	***1993***	***1994***	***1995***	***1996***	***1997***	***1998***	*1999*
Beaufond	+		+	+		+				
Bellemeade				+	+					
Blackwell	+	+	+	+	+		+	+		
Brauers	+		+		+					
Byrd Park	+									
Church Hill North								+		
Carytown								+		
Creighton							+	+		

Fairmont	+		+							
Fairfield			+							
Fairmont	+			+	+		+	+		+
Fulton								+		
Gilpin	+	+						+		
Green Park										+
Highland Park Southern Tip								+	+	+
Hillside Court		+			+					
Jackson Ward						+				
Oak Grove		+			+					
Old Town Manchester						+				
Monroe Ward						+				
Mosby	+		+	+		+		+		+
Northern Barton Heights										+
Randolph	+			+	+					
Southern Barton Heights								+		
The Fan	+			+	+			+		
Union Hill							+			+
Virginia Union										+
Whitcomb		+			+	+				
Windsor		+	+	+	+	+	+			
Woodville			+					+		

+ : Neighborhoods, in a way, exposing homicide hotspot(s) in at least one year.

All the homicide hotspots exposed in the similar neighborhoods might indicate significant clusters in the neighborhoods across the city. Moran's I statistics also confirms these descriptive hotspots visualization with positive spatial autocorrelation values in Table 4.20 below.

Again, these are just descriptive maps to understand the geographic distribution of the incidents. However, these maps for the hotspots provide the researcher with a solid perspective to realize the most problematic neighborhoods with respect to repeatedly experiencing homicide hotspots over the years. Then, this study needs to construct additional multivariate statistical models to comprehend the underlying structural reasons of having hotspots with respect to neighborhood disorganization. It, therefore, explores the association between the change in the neighborhood crime and the change in the neighborhood social disorganization over the years.

Figure 4.11: Annual Homicide Hotspots Overlaid Across Neighborhoods from 1990 to 1996

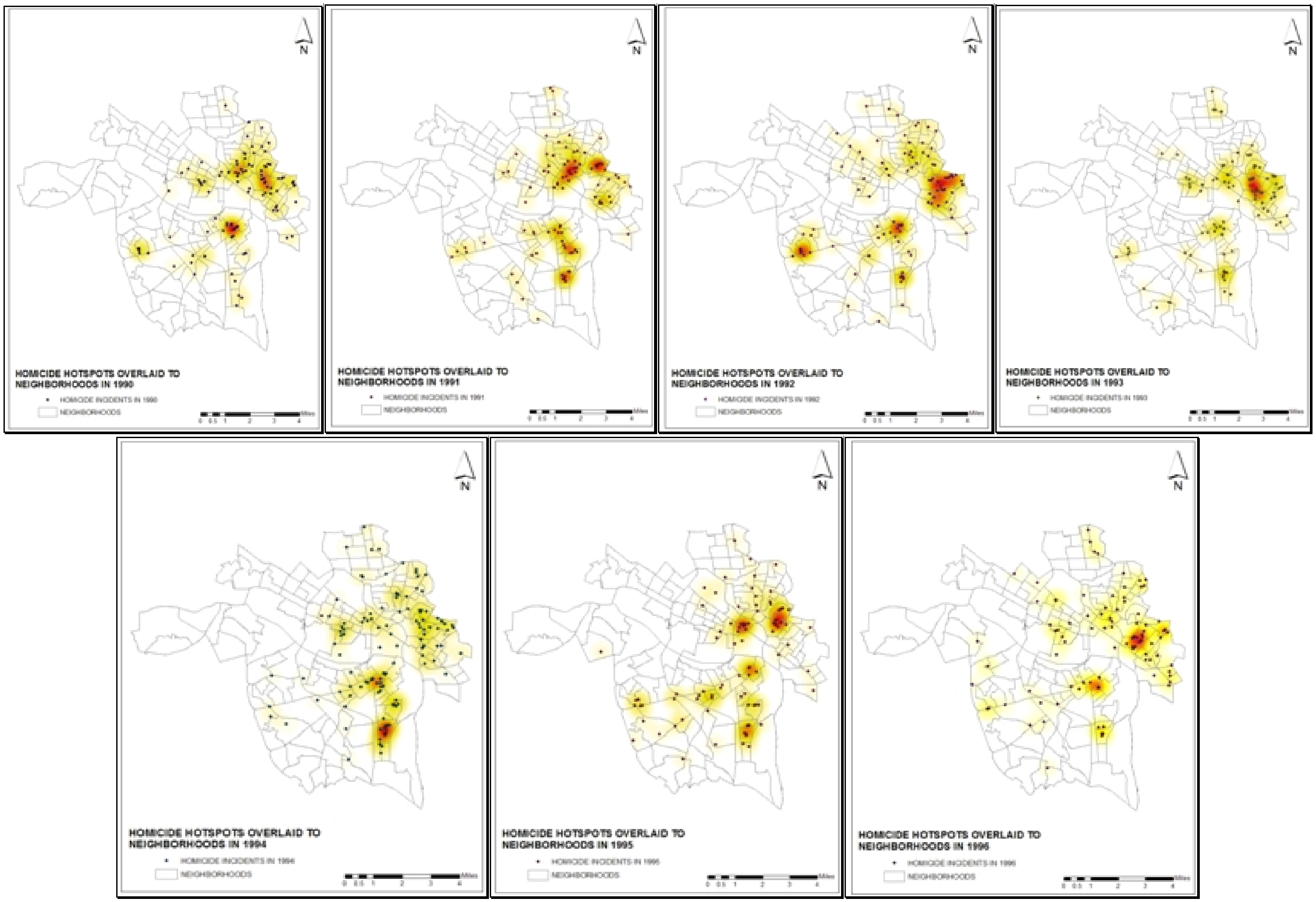
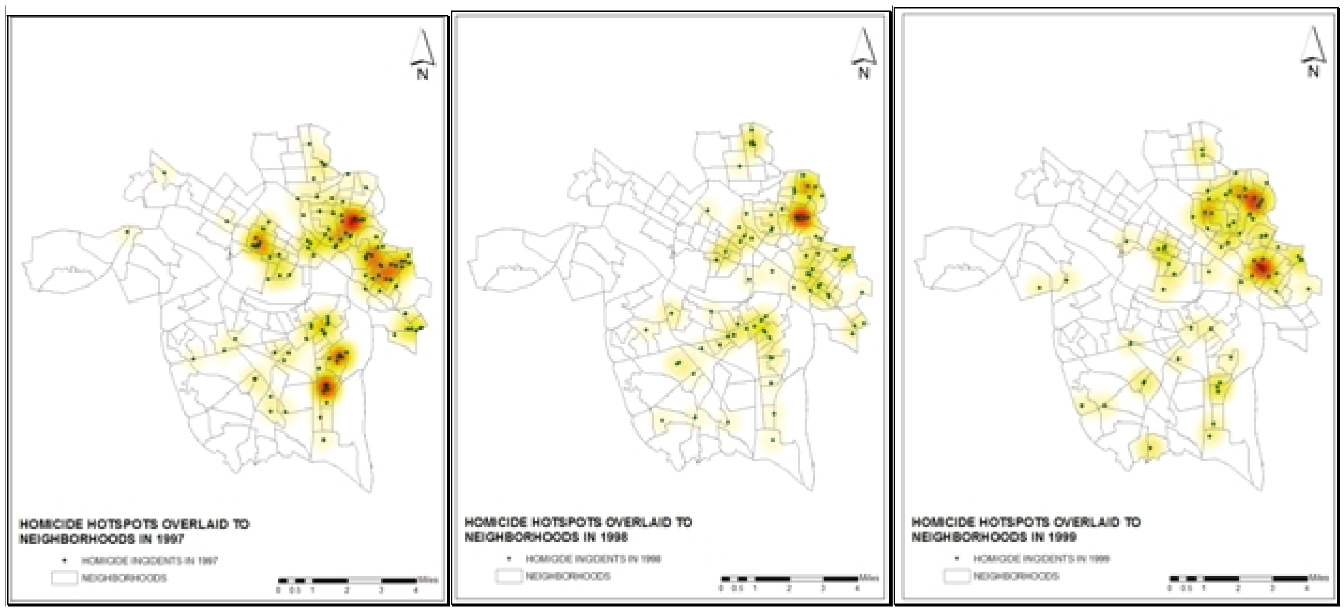


Figure 4.12: Annual Homicide Hotspots Overlaid Across Neighborhoods from 1997 to 1999



Moran's I Statistics and Spatial Autocorrelation

As discussed above, Moran's I statistics are computed to verify the results of descriptive homicide incidents hotspots analyses (Figure 4.11 & 4.12), and to show the existence of spatial autocorrelation (Table 4.20) across the neighborhood homicide rates.

Table 4.20: Global Moran's I Statistics for Neighborhood Homicide Hotspots

YEAR	*MORAN'S I STATISTICS**
1990	0.3003
1991	0.2737
1992	0.1658
1993	0.3088
1994	0.2589
1995	0.2430
1996	0.1379
1997	0.2615
1998	0.1293
1999	0.1699

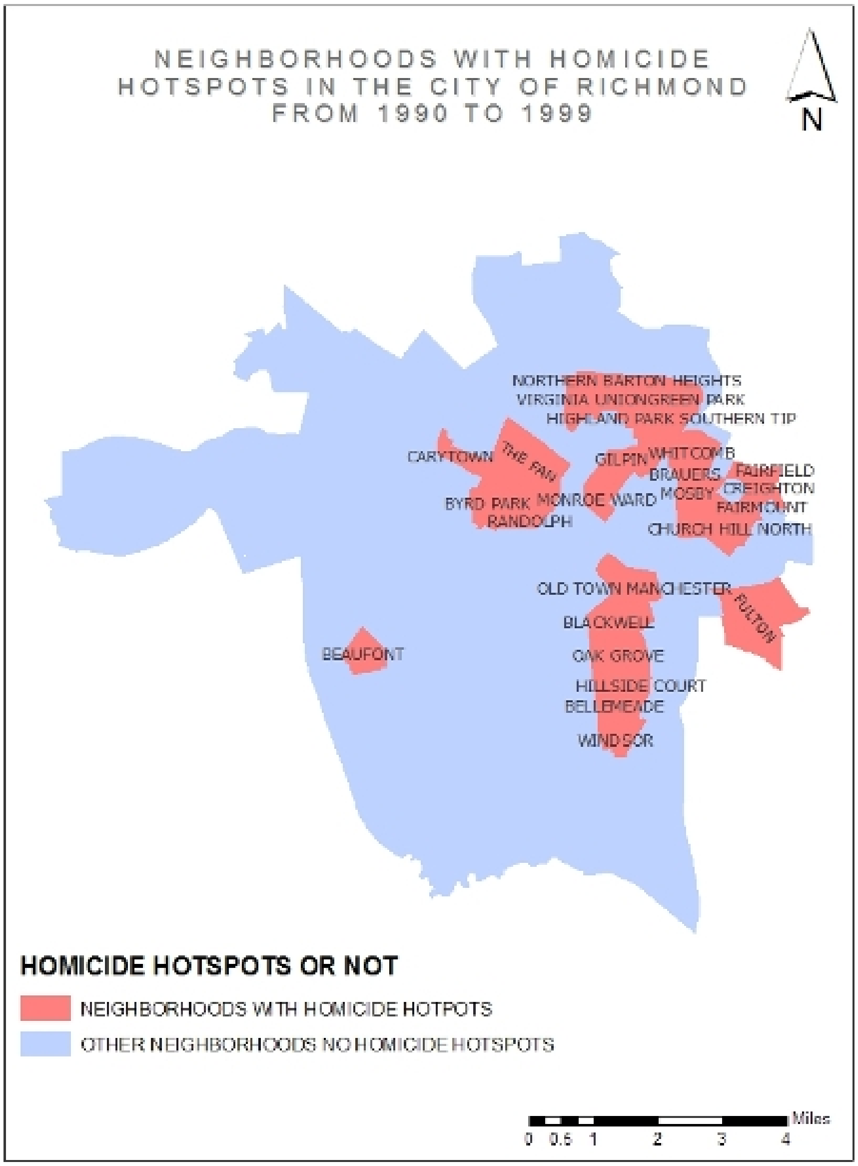
* $p \leq 0.05$

As explained in the previous chapter, Moran's I statistics are reasonably chosen since this study only deals with continuous level of measurements for its variables. Moran's I statistics, therefore, allow the researchers to calculate the deviation from spatial randomness, and become the most appropriate method for global spatial dependency in this study. For simple interpretation, positive values for Moran's I indicate positive spatial dependency, and vice versa.

According to the Table 4.20, global Moran's I statistical values all indicate that neighborhood homicide rates have become spatially clustered in each year. In fact, each homicide rate distribution across the neighborhoods has positive spatial autocorrelation for each year. Meaning that, neighborhoods are similar to each other in terms of having homicide rates. The neighborhoods with higher homicide rates seem contiguous with the ones having higher rates in each year. Likewise, the neighborhoods with lower homicide rates have also become contiguous with the ones having lower homicide rates. It can be concluded that, homicide incidents in the City of Richmond, are more likely to be dependent on the ones observed in contiguous neighborhoods across the city. As clearly seen in hotspots maps above, homicide hotspots have diffusively moved from one neighborhood to another, but still, the ones having high homicide rates tend to come together over the years. Accordingly, homicides in the City of Richmond are not randomly distributed over the years. And hypothesis about spatial randomness is evidently rejected.

Figure 4.13 illustrates all neighborhoods identified if they are, at least one time, victimized by homicide hotspots over the period between 1990 and 1999. With the help such resulting map, this study determines to establish a multiple regression model for these neighborhoods (in terms of Census block groups) as it more deeply analyzes these targeted neighborhoods only for the public policy consideration in the City of Richmond.

Figure 4.13: Neighborhoods* with Homicide Hotspots form 1990 to 1999



* These neighborhoods are included if they expose, at least one time, homicide hotspot during the time interval between 1990 and 1999.

Multiple Regression Analysis for Sub-Selected Neighborhoods with Homicide Hotspot(s)

The neighborhoods (N = 66 in terms of Census block groups as neighborhood proxies) having homicide hotspot(s), illustrated in the Figure 4.13, have been used to construct the multiple regression model in this section. In fact, this study wants to explore the association between structural covariates and homicide rates in these sub-selected neighborhoods over the entire years. In this line of reasoning, it computes the average values of all independent variables and dependent variable over 10 years. It has already examined many different statistical models for each so far. Now, it is sensible to focus only these neighborhoods for the entire period.

Stepwise multiple regression is used to reveal the significant variables that explore the variation within the average of neighborhood homicide rates in ten years. This model includes N = 66 census block groups, as the proxies of the neighborhoods, in the City of Richmond. Stepwise regression is used in the exploratory phase of research or for the purposes of pure prediction. Stepwise multiple regression, also called *statistical regression*, is a way of computing regression in stages. In stage one, the independent variable best correlated with the dependent variable is included in the equation. In the second stage, the remaining independent variables with the highest partial correlation with the dependent, controlling for the first independent variable, is entered. This process is repeated, at each stage partialling for previously entered independent variables, until the addition of a remaining independent variable does not increase R-square by a significant amount, or until all variables are entered (Tabachnich and Fidell 2001).

The prerequisite assumptions have been checked before constructing stepwise multiple regressions model. The data set has been examined in terms of its outliers and errors. There are no problematic outliers that might affect the regression models. The multicollinearity is not problematic since there are no excessively high correlated variables in the model. Tolerance scores in the regression model do not converge to zero either. In terms of normality and linearity, this study has not realized any issues for the linearity and normality although youth variable seems little problematic. However, this study does not see any compelling reason to make any transformations so as to avoid from additional layer between the results and the interpretations. The transformations would make the interpretations more complicated in the multiple regressions. Accordingly, the assumptions are conveniently met for the final multiple regression model.

All stepwise models are significant at p = .000. Table 4.21 illustrates how much variation within the average homicide rates over the 10 years are explained by the R-square (exploratory power of the model) in each subsequent model. However, model-3 in the Table 4.21 is the final version of the stepwise multiple regressions.

Table 4.21: Stepwise Multiple Regression Models[d] (See Appendix E)

Model	*R*	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*
1	.586[a]	.344	.334	.63560
2	.694[b]	.482	.465	.56926
3	.732[c]	.536	.514	.54283

a Predictors: (Constant), AVG_SES
b Predictors: (Constant), AVG_SES, AVG_PR_VACANT
c Predictors: (Constant), AVG_SES, AVG_PR_VACANT, AVG_PDENSITY
d Dependent Variable: AVG_HOM_RATE

The final model can explain almost 54% of the variance within the average homicide rate. The exploratory power of the model should be considered a moderately good model. According to the adjusted R-square, the model is not much penalized by the sample size such that both R-square and adjusted R-square scores are very close to each. R value in the model indicates strong relationships between average neighborhood social disorganization variables and the average homicide rate.

The Table 4.18 includes only the findings of final stepwise model. According to this table, this final model has no multicollinearity problem (Tolerance >.20; VIF <4). Unstandardized B values are the estimated regression coefficients (raw values). They give us the both direction and the magnitude of the coefficient. Over all, the final stepwise multiple regression model only includes the predictors that significantly explain the variation in the average neighborhood homicide rate ($p \leq .05$). This study needs to examine the Beta values to understand the relative contribution of each significant IV on DV. In fact, Beta values are the standardized coefficients, and unitless values in the regression model.

According to the beta values in the Table 4.22, therefore, AVG_SES has the highest contribution to explain the variation within the DV, whereas AVG_DENSITY (population density) has the lowest in this model. In other words, AVG_SES can explain almost 52% of the variance in the average neighborhood homicide rate *increases* in the neighborhoods having hotspot(s) as controlling the other average variables in the model. AVG_PR_VACANT can explain almost 32% of the variance in the average homicide rate *increases* in the neighborhoods having hotspot(s) as controlling the other average variables in the model. On the contrary, AVG_PDENSITY can explain almost 24% of the variance in the average homicide rate *decreases* in the neighborhoods having hotspot(s) as controlling the other average variables in the model. Accordingly, average SES and average percentage vacancy support the hypotheses, whereas average population density does not support.

Table 4.22: Final Stepwise Regression Model with Coefficients (See Appendix E)

	B	*Std. Error*	*Beta*	*Sig.*	*Tolerance*	*VIF*
(Constant)	.667	.210		.002		
AVG_SES	.413	.070	.519	.000	.973	1.028
AVG_PR_VACANT	.037	.010	.318	.001	.938	1.066
AVG_PDENSITY	-4.29E-005	.000	-.243	.009	.925	1.081

Dependent Variable: AVG_HOM_RATE

As Cahill (2004:31) challenges the role of population density in Social Disorganization Theory, it might be argued that greater population densities in the neighborhoods are more likely to enhance the levels of informal social control. Meaning that, more residents in neighborhoods might keep their eyes on their territories. In other words, negative association between population density and the homicide rate might be considered consistent with positive association between percentage vacancy and homicide rate. That is, murderers are most likely to prefer the neighborhoods with higher vacancy rates and lower population density in the City of Richmond. Although population density did not confirm the hypothesis (As “population density” increases so does neighborhood crime), the result might still be useful for the policy consideration in the City of Richmond.

Although this study could not realize any contribution of population density to influence the odds of having homicide across the entire neighborhoods in the logistic regression models, it feasibly reveals some contribution of the population density to explore the variation within the homicide rate in the neighborhoods having hotspot(s). One reason why this study could not realize the contribution of population density would be that the influence of population has been diluted across the entire neighborhoods (N = 163). And, most of the neighborhoods have not even experienced any homicide in separate years. For this reason, the variation of population density across the neighborhoods might not have been sufficient to influence the odds of homicide in the logistic regressions.

To close, this study constructed one more table (4.23) and one more figure (4.14) to better realize the overall findings with respect to whether the variables have supported the hypotheses in a series of multivariate statistical models such as binary logistics regressions, multinomial logistics regressions, and stepwise multiple regression.

Table 4.23 basically counts how many times one social disorganization variable supports the hypothesis. Meaning that, there has been positive association between neighborhood social disorganization variable and neighborhood crime in the City of Richmond.

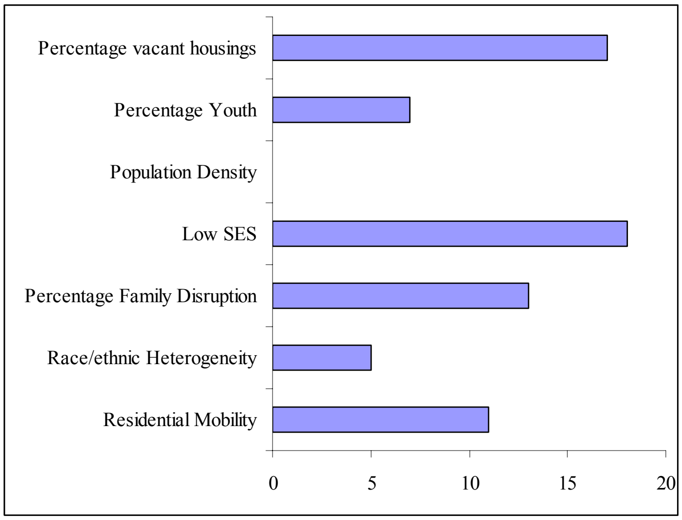
Table 4.23: List* of social disorganization variables positively influencing homicide increase in all multivariate statistical models

Variable	*Binary Logistics Over 11 models*	*Multinomial logistics Over 9 models*	*Multiple regression One model*
Residential Mobility	7	4	0
Race/ethnic Heterogeneity	2	3	0
Percentage Family Disruption	10	2	1
Low SES	11	6	1
Population Density	0	0	0
Percentage Youth	3	4	0
Percentage vacant housings	11	5	1

* Numbers are based upon how many times each variable has supported its hypothesis in this study

The Figure 4.14 also establishes a bar graphic to visualize the relative comparisons of neighborhood social disorganization. It basically plots how many times each neighborhood social disorganization variable has confirmed its hypothesis. Therefore, one can evidently realize which elements of neighborhood social disorganization are the most common to influence the homicide increase in the City of Richmond. Accordingly, the most common elements of neighborhood social disorganization include the low SES, vacant housings, family disruption, and residential mobility.

Figure 4.14: Relative comparisons of SDT variables



Summary of the Chapter

This chapter is mainly constructed by three phases, such as data preparation (both homicide and structural covariates), descriptive statistics/thematic mappings/hotspot analysis, and various multivariate statistical modeling. In fact, this chapter thoroughly constructs many binary and multinomial logistic regressions in multivariate framework. For instance, it uses binary logistics to test the expanded hypotheses of Social Disorganization Theory, including residential mobility, race/ethnic heterogeneity, family disruption, low SES, population density, youth, and vacancy. Likewise, it calculates their pure differences and uses them to construct difference models by Multinomial Logistics Regression. For the binary logistics models, it uniquely plots all odds ratio scores, and allows the research realize the most important variables. Accordingly, low SES, family disruption, residential mobility, and vacancy have become the most important variables to confirm the Social Disorganization Theory in the City of Richmond.

In MLR, this chapter comes with rational perspective to determine the essential time intervals as it investigates the association between change in neighborhood homicide and the change in neighborhood social disorganization. Notably, difference models are better fit with the longer time intervals such as 1990-99 and 1994-99 although other difference models with shorter time intervals also have provided good information about the differences. Among the difference models, change in low SES and change in vacancy have played consistently important role as testing the main hypothesis such as "Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time". Other important change variables that confirm the main hypothesis include change in youth and change in residential mobility over the years.

Finally, this study constructs stepwise multiple regression models on the very specific neighborhoods experiencing homicide hotspot(s) over ten years. The model has been constructed by the average values of both homicide rates and neighborhood social disorganization variables over ten years. With the advantages of the stepwise multiple regression, this study has successfully revealed three significant social disorganization variables (SES, vacancy rate, and population density) for the most vulnerable neighborhoods with respect to homicide in the City of Richmond, Virginia. The results of stepwise multiple regression have just confirmed the ones of logistic regressions so far.

Chapter 5

Conclusions and Policy Recommendations

Summary of the Study

The present study has specifically focused on both space and time aspects of neighborhood homicide distributions across the City of Richmond. Although this research can work with any *neighborhood crime*, as any type of index crime aggregated to neighborhood level, homicide has only been utilized due to limited accessibility for crime data in the City of Richmond. And, it has dealt with rareness of neighborhood homicide incidents, considered as a serious problem in the literature. To expand the perspective of Social Disorganization Theory (SDT), on the other hand, it includes additional social disorganization variables into the model Sampson and Groves (1989) developed. Nevertheless; rather than just rephrasing that social disorganization is associated with crime, this study attempts to show the consistency of SDT by the longitudinal research setting in the same city. Further, it investigates whether SDT supports the difference modeling such that the change in neighborhood homicide is more likely to be associated with the change in neighborhood social disorganization over time. As discussed in the policy recommendations, this study also acknowledges important policy programs implemented between 1990 and 1999, and makes some suggestions for them to improve their next wave implications from the view of SDT. It, therefore, interprets the findings in the light of both SDT and the outcomes of these policy programs such as Project Exile and Blitz-to-Bloom.

In other words, this study is primarily concerned about inferentially testing SDT, and expanding the SDT by constructing difference models over time. This study has three subsequently related research questions; (1) Is neighborhood homicide associated with social disorganization? (2) Which elements of social disorganization have the largest impact on neighborhood homicide variation? (3) Does the change in neighborhood social disorganization explain the change in neighborhood homicide over time? Accordingly, it constructs and verifies its seven hypotheses (residential mobility, race/ethnic heterogeneity, family disruption, socio-economic status, population density, youth, and vacancy) to test Social Disorganization Theory, while it establishes and confirms its main hypothesis such as "Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time."

Social Disorganization Theory (SDT) fundamentally deals with the characteristics of neighborhoods (communities), and attempts to reveal informal social controls in relation to the degree of social disorganization. SDT, therefore, evaluates neighborhood(s) as one unique personality having common values and attributes across the city. That is, some neighborhoods might be known by their unique characteristics. From this perspective, social ecologists focus on the neighborhoods (as a representative geography for the community) rather than individuals. In other words, SDT aims to understand the possible breakdowns of informal social controls amongst the community such that less informal social control might result in more socially disorganized neighborhoods. It ultimately determines that the more social disorganization the higher rate of crimes in neighborhoods (Shaw and McKay, 1942; Sampson and Groves, 1989).

Due to the limited crime data availability in the City of Richmond between 1990 and 1999, this study only deals with homicide. On the other hand, homicide has been very distinctive violent crime, and has been repeatedly questioned in the City of Richmond. In fact, this study becomes a unique study that works with homicide at neighborhood level. That is, most studies in literature did not prefer to investigate homicide pattern changes in relation to neighborhood social disorganization since they are very rare events to construct robust statistical models in the neighborhoods. Rather, they have worked homicide at city level or larger scales. This study contends that lack of studies for homicides at neighborhood level should be considered a serious gap in the literature, and it attempts to fill such deficiency by specifically using neighborhoods (Census Block Groups as proxies in this study) as a unit of analysis for the homicide, and further constructing difference models with Multinomial Logistic Regression. Ultimately, this study makes sub-selections out of all neighborhoods having homicide hotspot(s) over ten years, and construct a new stepwise multiple regression model on these neighborhoods only. It, therefore, determines the most vulnerable neighborhoods with respect to homicide as well as the most important social disorganization variables (the low SES, percentage vacant housings, and percentage population density) for these neighborhoods. In this line of reasoning, this study comes with such a solid research design and analytical methodology for the purpose of the research.

Speaking about the general research design, this study constructs a longitudinal research design with 10 years time steps, and uses Census 1990, Census 2000, and neighborhood homicide as a secondary data. Nonetheless, this study uses only two main census decennial years to calculate the other years' structural covariates by the linear interpolation technique such that this study is able to include these additional years to construct the essential difference models. To normalize the Census 1990 with Census Block Group geography for Census 2000, it utilizes the methodology GeoLytics (See Appendix A) developed. Otherwise, no one can construct difference models due to the lack of compatibility between the neighborhoods' boundaries in 1990 and the neighborhoods in 1999. This study uses 1999 instead of 2000 to compute the change processes for both neighborhood crime and neighborhood social disorganization since the actual Census 2000 data were gathered in 1999, but distributed in 2000.

Population includes all neighborhoods in the City of Richmond such that this study works with entire population, but no sampling procedure. Therefore, levels of significance are not relevant to reject the null hypotheses. Instead, this study only focuses on odds ratio scores of each predictor as it verifies the alternative hypotheses. Neighborhoods are the unit of analyses in this study. Each structural covariate and their different versions as social disorganization variables are independent variables, whereas neighborhood homicide with different versions (e.g., dummy form, three categories, and rate) is dependent variable in this study.

To avoid from multicollinearity and inconsistent error variance in the longitudinal setting, this study establishes factor loadings for residential mobility (Percentage of occupied households living in the same house for less than 5 years, and percentage of rental occupied housings) and low SES (Percentage of population below poverty line, percentage of households having public assistance, and percentage of unemployed individuals in civilian labor force).

In terms of validity and reliability issues, the present study attempts to confirm the previous findings of existing SDT literature in different population, the city Richmond. Further confirming the SDT with difference models is also more likely to meet the reliability and validity concerns. Therefore, it is pretty much satisfied with the reliability in this research. Using UCR data also enhances the reliability since the Police departments are supposed to follow certain rules and procedures to maintain their crime data in their database. Since they have to correctly and consistently report the crime data to FBI in each year, this study, as previous researchers, validates, and relies upon the quality of the official crime data. Using very similar conceptual model, but developed version, allows this study assure about relevant conceptualization, suitable operationalization, and measurements together. It is, therefore, satisfied with the construct validity as well. Dummy variables (for crime policy programs in the City of Richmond) as control variables in some years and time ranges might also make sure about the empirical validity in this study. Taken together, the analytical and conceptual approach in this study can, therefore, be implied in different cities like the City of Richmond.

Accordingly, the present study has successfully contributed to the literature around Social Disorganization Theory, social crime prevention, and spatially integrated crime policy analysis. Its conceptual model, solid research methodology, and its findings should be considered confirmatory for the Social Disorganization Theory in the City of Richmond, the homicide in relation to structural context, and policy considerations.

Limitations

This study recognizes certain limitations through conducting the entire research. These are;

- Longitudinal studies at neighborhood level are limited to Census decennial year's data set. Such studies, including the present one, are limited to census geography to operationalize their neighborhood definitions across the city. Worse, census geography in 1990 does not coincide with the census 2000. Studies, therefore, need to resolve this issue, and make the neighborhoods' boundaries compatible to go forward in longitudinal research setting.

- This study particularly has limited itself to the degree of social disorganization instead of all other neighborhood characteristics in the City of Richmond. It, therefore, does not account for situational indicators and collective efficacy covariates. Instead, it only focuses on structural covariates for social disorganization and their changes across the neighborhoods. Therefore, it is limited to one solid theory to investigate the space and time aspects of neighborhood crime, such as Social Disorganization Theory.

- Due to the changes with crime recording systems (UCR & NIBRS) in U.S., this study has been limited to certain period of time. Therefore, it aims to work with consistent and comparable neighborhood crime data over the years. Using only UCR also limits the number of time steps in longitudinal research. In fact, the crime recording system has changed from UCR to NIBRS in the City of Richmond since 2000.

- Although this study acknowledges positive spatial autocorrelation for the homicide rates (number of homicide incidents per 1000) across the neighborhoods, it cannot include any spatial parameter to both binary and multinomial logistics regression models. That is the limitation of spatial regression analysis such that dependent variable has to be at continuous measurement level and have sufficient variation to fit spatial regression model. In this study, rareness is much more important to cope with than fixing spatial autocorrelation. Such trade off between rareness and spatial autocorrelation should also be considered a limitation in this study. Positive spatial autocorrelation addresses that neighborhoods are similar to each other in terms of having homicide rates across the city (Figure 4.11). In other words, the neighborhoods with higher homicide rates seem contiguous with the ones having higher rates in each year, and vice versa. However, this study takes the advantages of acknowledging spatial autocorrelation, and ultimately focuses on very specific neighborhoods experiencing homicide hotspot(s) over a 10 year period.

- Neighborhood level studies are limited to certain conceptual and operational definitions for the actual neighborhoods in the city. The researchers, therefore, use proxies to operationalize the neighborhoods as the present study utilize Census Block Group as a neighborhood proxy. Clearly, these proxies are limited to Census geography since the Census can provide the richest information about the structural covariates.

Major Findings

This study has reached very important findings by the combination of both descriptive statistics/mapping approach and inferential statistics with multivariate approach. Findings should be interpreted by analytically processing these two types of information. Descriptive statistics and thematic mappings with standard deviations illustrate that communities are significantly different than each other across the city. Such structural variation also prepares theoretically convenient framework to study Social Disorganization Theory (Samson and Grove, 1989: 787). According to the descriptive statistics and hotspot analysis, homicide incidents are clustered in certain neighborhoods, whereas some neighborhoods have not experienced any homicide at all over the study period of time (Figure 4.11). In fact, 29 (twenty nine) arbitrary neighborhoods (but, they are 66 in terms of census block groups as neighborhood proxy in this study) have, somewhat, exposed homicide hotspots over this period. More specifically, Beaufond, Blackwell, Fairmont, Mosby, The Fan, Windsor neighborhoods are the most problematic neighborhoods with respect to homicide hotspots in the City of Richmond. Clearly, most of the neighborhoods having homicide hotspots in some degree are located in Bloom area. Binary logistic regression for the odds of having homicide, therefore, feasibly informs about the most important characteristics of these neighborhoods. It should be interpreted that such distinguished social disorganization variables be attributed to the neighborhoods experiencing homicide in each year.

Over all, Social Disorganization Theory has been consistently supported by some variables over the years. On the other hand, other variables support the theory in some degree. That is, some have supported SDT in certain years, but not other years. Major findings are reviewed in terms of each structural covariate below.

Residential Mobility was conceptually defined as the movement from one neighborhood to another. It was operationalized by establishing a composite proxy variable such as percentage of occupied households living in the same house for less than 5 years, and percentage of rental occupied housings. Originally, Shaw and McKay (1942) and Kornhauser (1978) contend communities may not establish common values to better live together if they move repeatedly move across the neighborhoods. And, Sampson and Groves (1989) have just supported them in their landmark study. Higher degree of residential mobility in the neighborhoods might increase the level of social disorganization, and therefore result in more neighborhood crimes from the perspective of SDT. In this study, residential mobility has supported the SDT hypothesis, except in 1990, 1992, 1993, and 1994. In fact, as residential mobility increases so does the neighborhood homicide. Residential mobility is, therefore, positively related with homicide in the City of Richmond for most years as previous studies found in the literature.

On the other hand, magnitudes of residential mobility to influence the homicide are much more than what Samson and Groves (1989) found in their studies. Their findings remained as marginal scores in their systemic model. When the residential mobility is negatively associated with the homicide as a violent neighborhood crime, it would be considered that SDT was not confirmed in some years. Nevertheless, some people living in minority neighborhoods might have not been able to afford to move for better neighborhoods (Roh, 2005). In this case, even if residential mobility could be lower, these neighborhoods might have experienced more homicide. Another approach would be that neighborhoods having more residential mobility might have received much more affluent residences. Residents with higher SES in the neighborhoods exposing higher level of residential mobility might also result in less homicide. Accordingly, residential mobility should be contingent with the SES and other unique characteristics of the neighborhoods. Speaking about the motive of the murders, they may not have found any target people any more in the neighborhoods having higher residential mobility.

Some residents might move into other neighborhoods so as to achieve their social capital. Otherwise, they may justify themselves to commit more neighborhood crime. The degree of residential mobility might maximize spatial dynamics of neighborhood social disorganization in the City of Richmond. In fact, homicide hotspots dynamically move from one neighborhood to another. However, the hotspots have been observed in the same neighborhoods in spite of the fact that they move around.

Race/ethnic heterogeneity conceptually addresses the degree of diversity among the racial and ethnic groups in the neighborhoods. Blau's (1977: 78) interaction index was used to operationalize the degree of such diversity. From the perspective of SDT, racially and ethnically diverse communities might be reluctant to develop informal social control in their neighborhoods. On the contrary, *race/ethnic heterogeneity* has not supported SDT in the City of Richmond over most years. This is unexpected result with respect to SDT. And, this is very unique situation in the City of Richmond as compared the previous findings of the literature. In fact, this study expected more homicides in more heterogeneous neighborhoods.

One reason why this study realized such inconsistent result for the race/ethnic heterogeneity might be the lack of enough variation across the neighborhoods, and insufficient change from 1990 to 1999. Another approach would be that neighborhood residences have got familiarized with themselves over time even though they are from different race/ethnic groups. The most problematic neighborhoods having higher homicide rates and/or hotspot(s) are not so heterogeneous neighborhoods such that they might have only one type of race/ethnic group.

In other words, these problematic communities with respect to homicide are identified as more isolated groups compared to the rest of the city. These neighborhoods have also highest poverty rates (Figure, 4.4) in the City of Richmond. Especially north eastern side of the city is concentrated with African American residences. Since the homicide incidents mostly occur in such homogenous neighborhoods, race/ethnic heterogeneity might not have confirmed the SDT in the City of Richmond. However, isolated African American neighborhoods with higher poverty verifies Wilson's (1987) thesis such that these should be considered as socially disadvantaged neighborhoods.

These isolated neighborhoods might, therefore, have deviated from the mainstream of the city. Although race/ethnic heterogeneity did not explain the distribution of neighborhood homicide, isolation with higher poverty in certain neighborhoods becomes more important issue in the City of Richmond.

Family disruption conceptually addresses instability of the families in the neighborhoods in terms of either divorce, separation, female-headed household with children, or all together. In this study, the family disruption was operationalized by only female-headed households with children, as commonly used in the literature. From the perspective of SDT, Sampson and his Colleagues (1986; 1997; and 2003) focused on the role of family disruption that might weaken the degree of informal social control in the neighborhoods. They also contend that married families are more likely to protect their children, and to develop informal social control in their neighborhoods. In this study, family disruption has supported SDT although its contribution to influence the odds of having homicide remains very low. In fact, it has been able to change only 1-3% of the original odds of having homicide across the neighborhoods (Table 4.18; Figure 4.13). Anyway, the results confirm what Sampson and Groves found for the family disruption.

Socio-economic status is conceptually defined as low economic conditions refer to scarcity of money and resources (Samson and Groves, 1989). It was operationalized by establishing a composite variable that includes percentage of population below poverty line, percentage of households having public assistance, and percentage of unemployed individuals in civilian labor force. From the perspective of SDT, absence of essential resources to enhance their community might also weaken the social control and networks in the neighborhoods. Low SES has been the most important social disorganization proxy in this study. That is, it has been able to predict at least 40% of the odds of having homicide across the neighborhoods in all years. Therefore, it confirms what previous studies have found in the literature.

Population density is conceptually defined as "a heavy concentration of people residing in an area" (Paulsen and Robinson, 2004: 62). It was operationalized by the ratio of number of people living in a neighborhood to its area (# of people / area of neighborhood) in this study. From the perspective of SDT, higher population density might be an important source to amplify the level of social disorganization in the neighborhoods. Interestingly enough, *population density* has not supported SDT for any hypotheses by either binomial or multinomial logistic regression analyses in the City of Richmond. In the exploratory approach, however; stepwise multiple regressions model has been able to verify the contribution of population density in very specific neighborhoods experiencing homicide hotspot(s) over 10 years. I think, the City of Richmond has homogenous population density across the neighborhoods, and has not significantly changed over time (Table 4.3 and Figure 4.5). Such insufficient variance across space and time did not result in explanatory power to influence the odds of having homicide in the neighborhoods in the City of Richmond.

Youth is additionally included to the conceptual model Sampson and Groves (1989) developed in this study. Young population in higher heterogeneous neighborhoods might become more important predictor to determine neighborhood crime variation. In fact, young people from different race/ethnic background are less likely to develop informal social control in their neighborhoods. The neighborhoods having higher family disruption can also make the young predictor more important to delineate the degree of informal social control. In this study, young did not confirm the SDT in all years, except in 1999. However, it was able to influence the only 3% of the odds of having homicide across the neighborhoods in the City of Richmond.

Vacancy rate is also additionally included into the model Samson and Groves (1989) developed in the literature. From the perspective of SDT, higher vacancy rate might indicate higher disorganized neighborhoods in some degree. It was operationalized by the percentage of vacant housings over the total number of housings in this study. Vacancy rate, therefore, has consistently supported SDT in the City of Richmond although its contributions remain marginal in some years. It makes sense to the research since offenders might have mostly preferred to murder somebody in the neighborhoods having higher vacant buildings. It is less risky. This finding should be considered the intersection of opportunity theories and SDT in the literature. In the concentrated neighborhoods with respect to having homicide hotspots, higher vacant housing rates seem consistent with less population density to influence the variation within homicide rates. In fact, the vacancy rate is positively associated with the homicide rate, whereas the population density is negatively associated with homicide in the concentrated neighborhoods.

The main hypothesis has been verified in various difference models constructed by Multinomial Logistic Regression (MLR). Each change score for seven social disorganization variables have been computed and included as new structural covariates in the MLR. Homicide rates (as dependent variable) have also been recoded into three different categories such as “no change”, “decrease’, and “increase” for the difference models. This study has, therefore, been able to construct new multivariate statistical models (like multinomial logistic regression) to verify the main hypothesis from the perspective of SDT in a longitudinal framework. Each essentially convenient time range was rationally determined by examining the homicide trend analysis (Figure 4.1). Of the time intervals, one year difference models have not performed a good job to explore the association between the change in homicide and the change in neighborhood social disorganization over time. This result is sensible since neighborhood change cannot be realized in such short terms. Other difference models with two or more year’s intervals have provided additional information to determine whether one unit increase in the level of social disorganization can explain the certain degree of increase in the odds of having homicide across the neighborhoods. The increases in *low SES* and the increases in *vacancy rates* are determined the most important contributors to influence the odds of homicide increase across the neighborhoods in most time ranges. The increase in *residential mobility* and the increases in *youth rate* have also explained, to some degree, the changes in the odds of homicide increase across the neighborhoods in certain time intervals. For instance, the residential mobility has influenced the certain degree of the odds in the following ranges: 1990-99, 1994-99, 1996-97, and 1997-99. The vacancy rate change, on the other hand, has been good predictor in 1990-94, 1993-94, and 1996-97. The change in family disruption and the change in population density, as in binary logistic regression models, did not support the main hypothesis in this study.

Taken together, difference models with MLR have further confirmed the SDT by examining the association between the change in neighborhood social disorganization and the change in homicide as a neighborhood crime. Another important point is that homicides are not randomly occurred across space and time. In this study, various forms of social disorganization covariates have been verified as possible underlying reasons for such non-random patterns over time and space. According to the different multivariate statistical models in this study, the most important social disorganization variables are listed below:

- The low SES
- Residential Mobility
- Vacancy
- Population Density (across only the concentrated neighborhoods)
- Family Disruption
- Youth rate (only change form only in the difference models)

Accordingly, the present research realized many homicide pattern changes across neighborhoods with respect to possible changes in these neighborhood social disorganization variables. Homicides are significantly clustered in certain neighborhoods, and these neighborhoods have got spillover effects on their contiguous neighborhoods over 10 years. That is, homicide hotspots have just been exposed in very specific neighborhoods while they move amongst these neighborhoods.

The next section, therefore, attempts to offer neighborhood-level policy considerations based upon the unique findings in this study and the views from the literature.

Policy Recommendations

Understanding the space and time aspects of neighborhood crimes is of great interest to policy and decision makers as they analyze the underlying structures of neighborhood crime incidents. In fact, they would like to reveal the association between the change in the neighborhood homicide (as one of the most problematic crimes in the City of Richmond, VA) and the change in community characteristics. From this perspective, this study offers the following policy considerations based upon its theoretically supported findings. As well as revealing the most important neighborhood social disorganization characteristics associated to homicide distribution in the City of Richmond, this section also argues some points about both Project Exile and Blitz to Bloom policy programs. The policy recommendations are offered for the City of Richmond, but similar policies might also be useful for the cities having similar structural characteristics with Richmond in the U.S.

1. Enhance hotspot policing strategies and construct a comprehensive crime mapping system in the City of Richmond:

This study verifies that homicide (as a neighborhood crime) hotspots are not randomly distributed in the City of Richmond. From the perspective of spatially integrated policy analysis, policing implications might be more effective and efficient if the police could use the "*processed information*" on neighborhood crime hotspots across the city. In fact, the City of Richmond needs an online crime mapping system integrated with spatial statistics and other useful analytical methodologies. This system can, therefore, detect the most vulnerable neighborhoods with respect to the neighborhood crime change attributed to the neighborhood social disorganization over time. That is, vulnerability of neighborhoods might dynamically vary depending on various policy implications and changes across the city.

Rather than only distributing thematic crime mapping, this system should also be integrated with other community level information from both official and unofficial actors (Birkland, 2001) of the public policy. Meanwhile, from the perspective of SDT, this system is supposed to target the communities and neighborhoods instead of individuals and families (Sampson, 2004: 243). Such spatially integrated analytical system, as a crime policy analysis tool, might be effective and efficient communication tool amongst the policy stakeholders as well. The City of Richmond Police Department can further enhance their "sector policing" by such comprehensively integrated community level information, and let the officials better know their territories they serve.

From this policy recommendation with the enhanced hotspot policing and a comprehensive crime mapping system, the City of Richmond Police Department should have their crime analysts trained with advanced GIS applications and other advanced analytical techniques such that they can plausibly process the integrated information to improve police decision making. Accordingly, the universities should be considered the best nexus to link practical policing experience, research oriented thinking, and elements of public policy analysis for neighborhood level crime issues.

Online mapping approach for crime prevention and community development together might allow the City to establish an enhanced decision support system. That is, the system might logically and analytically process all related information, and offer a dynamic *agenda* for the City officials. If the system could be further enhanced by intelligent components and knowledge discovery tools, then policy alternatives with this agenda might be more comprehensively evaluated for social crime prevention initiatives.

Neighborhood revitalization and stabilization programs:

This study verifies the importance of vacancy rate and residential mobility as it investigates the association between the level of neighborhood social disorganization and the neighborhood homicide. In fact, the percentage of vacant/abandoned housings increases so does the homicide across the neighborhoods in the City of Richmond. Likewise, Residential mobility increases so does the homicide in the neighborhoods. These neighborhood social disorganization factors should be considered contingent upon the low SES, family disruption, and youth population in the City of Richmond.

From the perspective of SDT, Sampson (2004:246) offers private/public intervention programs to enhance the social organization in these neighborhoods. In literature, instable population and increasing housing decay have been considered the source of having more social and crime issues in the concentrated neighborhoods with low socioeconomic status. From this perspective, the City of Richmond has invested on a very comprehensive neighborhood revitalization program and aimed to increase the ownership across the neighborhoods in the Bloom area (Accordino et al., 2005) since 1999. One of results in this program is that targeting specific neighborhoods maximizes the benefits of the investments, and therefore, targeted neighborhoods have become more stabilized by increasing the ownership for the purpose of this program. Accordingly, the neighborhoods' disintegration might reverse to the "neighborhood integration" by such community level policy interventions in concentrated low SES areas. From the perspective of SDT, communities having more ownership might have better opportunities to enhance collective efficacy among them as well. Such more stabilized communities might also establish more convenient environments for better youth socialization (Sampson, 2004: 247).

Taken together, this study guided by Social Disorganization Theory provides theoretical, methodological, and policy oriented contributions to the literature around spatially integrated social policy and law enforcement applications. That is, ecological concentration with higher degree of social disorganization allows the policy makers to offer tangible and rational solutions to enhance the informal social control in the problematic neighborhoods with respect to high neighborhood crime. With the feasible policy considerations, neighborhoods would become less vulnerable against neighborhood crime. However, specific findings in this study requires either a joint-force or task force against crime at neighborhood and/or city level if one accounts various dimensions of neighborhood crime phenomenon, including attributes of neighborhoods, enforcement efforts, and various policy implications.

Points for Project Exile and Blitz to Bloom:

Speaking about the Project-Exile and Blitz-to-Bloom policy programs in the City of Richmond, this study realizes several points to understand their contributions on the neighborhood homicide distribution as it verifies its main hypothesis (Neighborhood homicide increase is likely to be associated by the increase in neighborhood social disorganization over time) and other expanded hypotheses of SDT.

Unfortunately Project-Exile has not been included into the statistical models since it has a uniform impact on the neighborhoods. Difference models were not able to include the Project Exile as a dummy variable either. It is because its contribution is constant across all neighborhoods. However, homicide trend analysis confirms that there is a dramatic decrease just after the year Project-Exile was initiated in 1997. However, it might not be right to address causal relationships based upon such a trend analysis. Further, homicide hotspot analysis provides the research with detailed information at lower scales such as hotspot and/or neighborhood levels (Figure 4.11 and 4.12). In fact, the neighborhoods experienced much larger and more intensive homicide hotspot(s) in 1997. Next year, however, most homicide hotspots across the neighborhoods just disappeared due to *possible* influence of the program. However, the homicide hotspots in northeastern side of the city still keep remaining despite of the Project-Exile. According to the Figures from 4.1 to 4.7, these neighborhoods are more likely to become socially disorganized neighborhoods in terms of higher residential mobility, higher isolated (lower heterogeneity) race/ethnic groups, higher family disruption, lower SES, and higher vacancy rates. Consequently, although Project-Exile might have reduced the homicide rates citywide after 1997, socially disorganized neighborhoods still insist on experiencing higher neighborhood crime. The officials might want to consider increasing the awareness of such socially disorganized communities against crime as a disease for the society. And, the communities might be further educated to raise their awareness level. From the perspective of enhancing awareness, policy makers should reconsider the local implications of Project Exile for these most vulnerable neighborhoods as well as keeping its citywide implications. Therefore, before next wave of Project-Exile, these social disorganization variables might be reflected in concert with the policy implication.

Blitz to Bloom, on the other hand, allows the research to use its dummy form as a control variable in this study. It was only implied in specific neighborhoods of Bloom area. Both difference models and the binary logistic regressions model for the restructured neighborhood level data (1630 cases instead of 163 cases for a 10-year period) provide additional information about the Blitz to Bloom as compared to separate models in each individual year. Difference models could not confirm that Blitz to Bloom might have reduced homicide in these neighborhoods, whereas "ALL" model (by 1630 cases, and examining both within and between neighborhoods) verifies the contribution of this program to reduce the original odds of homicide as controlling the neighborhood social disorganization variables over 10 years. In fact, this model is able to influence the changes in the odds of homicide within the neighborhoods in Bloom area over the years. This should not be considered as the consequence of this program, but rather, consequence of time in the long run. Accordingly, such police crackdowns implied for specific neighborhoods in a limited period of time (6 months in the City of Richmond) may reduce the neighborhood crime for the short runs, but may not over all crimes citywide. This study cannot interpret further since it is limited to period between 1990 and 1999. It does not include or comprehend the changes of either neighborhood crime or social disorganization after 1999.

Future Directions

Future studies might focus on the following points and approaches for academic continuum;

- Include African-American population for the conceptual model in the City of Richmond: The results of the present study encourage future researchers to examine neighborhood crime associated with unique characteristics of such isolated communities in the City of Richmond.
- Land use variability might become valuable addition for the conceptual model in future research. That is, vacancy rate, as one of the land use classifications, has successfully explained the variation within neighborhood homicide. Other components of land use, such as commercial, educational, multi family, single family, public and open space etc., in the urban settings might significantly add explanatory powers of the statistical models in future studies.
- Include downtown neighborhoods as another control variable: This study realizes that homicide incidents occurred very rarely in downtown of the City (Figure 4.11 & 4.12). It might be because of having more security

implications, such as police, security systems, and private security guards, in the downtown environments. Accordingly, future researchers may want to consider classifying neighborhoods such as whether they are downtown neighborhoods or not.

- Include 2010 Census data to improve longitudinal settings for the purpose of similar study: Additional Census decennial year might allow the researchers construct full version of longitudinal research setting with advanced growth modeling.
- Include intervening dimensions of social disorganization: Survey research might be essential to study intervening dimensions of social disorganization in the City of Richmond. This might become interesting research opportunity to compare with what Sampson and his colleagues have done in Chicago neighborhoods. For longitudinal setting, it might be necessary to repeat such survey research as subsequent waves.
- Include more neighborhood crimes and compare them with respect to how these different crimes might be influenced by various neighborhood social disorganization variables in the City of Richmond. Although this study is limited to neighborhood homicide, conceptual framework and methodological approach might also be utilized for many other types of neighborhood crimes if they become accessible for the researchers.
- Replicate the same model and analytical methodology for the homicide only in different cities and compare the results: If methodological and

conceptual framework developed for neighborhood homicide in this study could be replicated for different cities, the results might provide policy makers and researchers with better generalized visions.

To close, this study verifies Social Disorganization Theory in different population (the City of Richmond) as it investigates the association between neighborhood social disorganization and homicide (as a neighborhood crime). It expands the conceptual model, Sampson and Groves (1989) developed, as feasibly adding new structural variables (youth and vacancy) and thoroughly constructing difference models to verify the association between neighborhood homicide change and social disorganization change.

List of References

Akers, R.L. (2000). Criminological Theories: Introduction, Evaluation, and Application. Third Edition. Roxbury Publishing Company.

Anselin, L. (1988). Spatial Econometrics: Methods and Models. Dordrecht: Kluwer Academic Press.

Anselin, L., Cohen, J., Cook, D., Gorr, W., & Tita, G. (2000). Spatial analyses of crime. In D. Duffee (Ed.) Measurement and Analysis of Crime and Justice; Criminal Justice 2000, (Vol. 4, pp. 213-262). Retrieved Nov. 6, 2005, from National Crime and Justice reference Service Web site: http://www.ncjrs.org/criminal_justice2000/vol_4/04e.pdf.

Bachman, R & Paternoster, R. (1997). Statistical Methods for Criminology and Criminal Justice. The Mcgraw-Hill companies.

Blau, P. M. (1977). *Inequality and heterogeneity: A primitive theory of social structure*. New York: Free Press.

Boba, R. (2005). Crime Analysis and Crime Mapping. Sage Publications, USA.

Boba, R. (2000). Guidelines to implement and evaluate crime analysis and mapping in law enforcement agencies. Community oriented policing services U.S. Department of Justice. [On-line]. Available: http://www.usdoj.gov/cops/pdf/cp_resources/ppse_pubs/e112k0774.pdf [February 12, 2001].

Brody, G.H., Ge, X., Conger, R., Gibbons, F.X., Murry, V.M., Gerrard, M., and Simons, R.L. (2001). The Influence of Neighborhood Disadvantage, Collective socialization, and parenting on African American Children's affiliation with deviant peers. Child Development 72(4);: 1231-1246.

Brantingham, P. L., & Brantingham, P. J. (1999). Theoretical Model of Crime Hotspot Generation. *Studies on Crime and Prevention*, *8*, 7-26.

Byrne,James M. and Robert J. Sampson. 1986. "Key Issues in the Social Ecology of Crime." Pp. 1-22 in *The Social Ecology of Crime*,edited by James M. Byrne and Robert J. Sampson. New York: Springer-Verlag.

Bursik, R.J., & Grasmick, H.G. (1993). Neighborhoods and Crime: The Dimensions of Effective Community Control. Lexington Books.

Butts, J.A. (2000). *Youth Crime Drop*. Urban Institute, Justice Policy Center.

[On-line]. Available: http://www.urban.org/UploadedPDF/youth-crime-drop.pdf [December 04, 2006].

Cahill, M. E. (2004). Geographies of urban crime: an intraurban study of crime in Nashville, TN; Portland, or; and Tucson, AZ. Retrieved Nov. 16, 2005, from NCJRS Web site: http://www.ncjrs.gov/pdffiles1/nij/grants/209263.pdf.

Cameron, J. G., & Leitner, M. (2005). Spatial Analysis Tools for Identifying Hotspots. *Mapping Crime: Understanding Hotspots (Special Report)*. U.S. Department of Justice. NIJ. Mapping & Analysis for Public safety (Maps).

Canter, P. (2000). Using a Geographic Information System for Tactical Crime Analysis. In (Ed.) Analyzing Crime Patterns: Frontiers of Practice by Victor Goldsmith, Philip G. McGuire, John H. Mollenkopf, Timothy A. Ross. US. Sage Publications, Inc.

Chainey, S., & Ratcliffe, J. (2005). GIS and Crime Mapping. England: Wiley.

Chainey, S., & Dando, J. (2005). Methods and techniques for Understanding Crime Hotspots. *Mapping Crime: Understanding Hotspots (Special Report)*. U.S. Department of Justice. NIJ. Mapping & Analaysis for Public safety (Maps).

Chamard, S.E. (2003). Innovation-Diffusion Networks and the Adoption and Discontinuance of Computerized Crime Mapping by Municipal Police Departments in New Jersey. Dissertation. Rutgers University.

Clarke, R.V. (1995). Situational Crime Prevention. *Crime and Justice*, Vol(19), 91-150. University of Chicago.

Cohen, L. & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. American Sociological Review, Vol(44):588–608.

Cohen, J., W. Gorr, & A. Olligschlaeger. (1993). Modeling Street-Level Illicit Drug Markets, Working paper 93–64, The H. John Heinz III School of Public Policy and Management. Pittsburgh: Carnegie Mellon University.

Collins, M.L. (2002). "An Elaboration and Analysis of Two Policy Implementation Frameworks to Better Understand Project Exile." Doctoral Dissertation. Retrieved March 1, 2006, from http://scholar.lib.vt.edu/theses/available/etd-12192002-110022/

Curley, M. A. (2005). Theories of urban poverty and implications for public housing policy. *Journal of Sociology and Social Welfare*, June.

Dawes, Sharon S. (1996). Interagency Information Sharing: Expected Benefits, Manageable Risks. Journal of Policy Analysis and Management 15(3): 377-94.

Eck, J.E. (2005). Crime Hotspots: What they are, Why We Have Them, and How to map Them. *Mapping Crime: Understanding Hotspots (Special Report)*. U.S. Department of Justice. NIJ. Mapping & Analaysis for Public safety (Maps).

Elliott, D. S., Wilson, W. J., Huizinga, D., Sampson, R. J., Elliot, A., and Rankin, B. (1996). The effects of neighborhood disadvantage on adolescent development. Journal of Research in Crime and Delinquency, 33(4):389–426.

Fotheringham, A.S., Brunsdon, C., and Charlton, M.E., 2002, *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*, Chichester: Wiley.

Garson, D.G. & Vann, I.B. (2001). Geographic information Systems for Small and Medium Law enforcement Jurisdictions: Strategies and Effective Practices. [On-line]. Available: http://www.gcc.state.nc.us/gispage/ep1.htm [September 30, 2004].

Getis, A. et al., 2000. Geographic Information Science and Crime Analysis. URISA Journal, 12(2): 7-14.

Godfrey, E. Drexel and Don R. Harris. (1971). Basic elements of intelligence. Washington, D.C.: U.S. Government Printing Office.

Gottlieb, S., Arenberg, S., & Singh, R. (1994). Crime Analysis from first report to Final arrest. California, US: Alpha Publishing.

Greene, R.W. (2000). GIS in Public Policy: Using Geographic Information for more Effective Government. Esri.

Groff, E., & LaVigne, N. (2001). Mapping an opportunity surface or residential burglary. *The Journal of research in Crime and Delinquency*, 38 (3): 257-278.

Haley, K.N., Todd, J.C., & Stallo, M. (1998). Crime analysis and the struggle for legitimacy. Unpublished and presented at ACJS Annual Meeting. [On-line]. Available: http://www.iaca.net/resources/FAQs/FAQ%20…..20Struggle%20for%20Legitimacy.htm

Hamilton, E.E. (2004). Prelude to Project Safe Neighborhoods: the Richmond, Virginia, Experience. Police Foundation reports, January. Washington, DC.

Hannon, L.E., & College, O. (2005). Extremely Poor Neighborhoods and Homicide. Social Science Quarterly, Vol. 86, pp. 1418-1434.

Harries, K. (1999). Mapping crime: Principle and practice. Retrieved Sep. 16, 2005, from NCJRS Web site: http://www.ncjrs.org/html/nij/mapping/pdf.html [September 14, 2005].

Hirschfield, A., Yarwood, D. and Bowers, K. 1997 'Crime Pattern Analysis, Spatial Targeting and GIS: The development of new approaches for use in evaluating Community Safety initiatives.', in N. Evans-Mudie (ed) Crime and health data analysis using GIS, Sheffield: SCGISA.

ICPSR Inter-university Consortium for Political and Social Research, National Incident-Based Reporting System, 2000 United States Department of Justice Federal Bureau of Investigation ICPSR 3449

Hirschfield, A. (2001). Decision Support in Crime Prevention: Data Analysis, Policy Evaluation and GIS. In (Ed.) Mapping and Analyzing Crime Data: Lessons from research and practice. Pp. 237-268.

Innes, J.E & Simpson D.M. (1993). Implementing GIS for planning. Journal of the American Planning Association 59(2):230-237.

Johnson, S. Heineman, E., Smith, T., Walko-Frankovic, D., & Willard, T.B. (2001). Evaluation of the Virginia Exile Program: Final Report. Department of Criminal Justice Services: Criminal Justice Research Center, Evaluation Unit. Richmond, VA.

King, Gary & Langche Zeng. "Logistic Regression in Rare Events Data," Political Analysis, Vol. 9, No. 2 (Spring, 2001): 137–163.

Kornhauser, R. R. (1978). Social Sources of Delinquency. University of Chicago Press, Chicago.

Krivo, L.E., & Peterson, R.D. (2000). The structural Context of Homicide: Accounting for Racial Differences in Process. *American Sociological Review*, Vol. 65, No. 4. (Aug., 2000), pp. 547-559.

Kubrin, C.E, and Weizer, R. (2003). New Directions in Social Disorganization Theory. Journal of Research in Crime and Delinquency, 40(4), 374-402.

Lance, E.H., & College, O. (2005). Extremely Poor Neighborhoods and Homicide. Social Science Quarterly, Vol (96). Southwestern Social Science Association.

Land, Kenneth C., Patricia L. McCall, and Lawerence E. Cohen. (1990). “Structural covariates of homicides rates: Are there any invariance across time and social space?” *American Journal of Sociology*. 95(4), p. 922-63.

Lander, B. (1954). Towards Understanding of Juvenile Delinquency. New York, Colombia University.

Lenz, R. (1986). Geographical and temporal Changes among Robberies in Milwaukee, pp.97-115. In Metropolitan Crime patterns, (ed), Figlio, R.M., Hakim, Simon., and Rengert, G.F.

Lopez, X. (1996). The Impact of Government Information Policy on the Dissemination of Spatial Data. PhD Diss., University of Maine.

Lowenkamp, C.T, Cullen, F.T., and Pratt, T.C. (2003). Replicating Sampson and Groves’s test of social Disoarganization theory: revisiting a criminological Classic. *Journal of research in crime and delinquency*, 40(4) November 2003: 351-373.

Luongo, A. J. (2005). Gone in sixty seconds: examining motor vehicle theft in motor vehicle theft in Philadelphia. Retrieved Nov. 28, 2005, from Mapping & Analysis for Public safety Web site: http://www.ojp.usdoj.gov/nij/maps/savannah2005/papers/Luongo.pdf.

Lynch, J. P., & Addington, L. A. (2007). *Understanding crime statistics: revisiting the divergence of the NCVS and UCR*. Cambridge studies in criminology. Cambridge University Press.

Majone, G. 1990. “Policy Analysis and Public Deliberation” in *The Power of Public ideas*. Cambridge, Massachusets: Harvard University Press. pp. 157-178.

Masser, I. (1998). Governments and Geographic Information. Taylor & Francis Ltd.

Massey, D. S, and Denton, N. A. (1988). The dimension of residential segregation. *Social Forces*, Vol(67**)**: 281-315.

Mertler, C.A., & Vannatta. (2005). Advanced and Multivariate Statistical Methods: Practical and Interpretation (3rd Ed.). Pyrczak Publishing, Glendale, CA

Messner, S.F., Anselin, L., Baller, R.D., Hawkins, D.F., Deanne, G., & Tolnay, S.E. (1999). The Spatial Patterning of County Homicide Rates: An Application of Exploratory Spatial Data Analysis. *Journal of Quantitative Criminology, Vol. 15, No. 4.*

McMillan, J. (2004). *Educational research: fundementals for the consumer*. Fourth edition ed. Boston: Pearson.

Menard, S. (1991) *Longitudinal Research*, Newbury Park: Sage Publications.

Morenoff, J. D., & Sampson, R. (1997). Violent crime and the spatial dynamics of neighborhood transition. *Social Forces, 76*(1), 31-64.

Morenoff J.D., Sampson, R.J., Raudenbush, S.W. (2001). Neighborhood inequality, collective efficacy, and the Spatial Dynamics of Homicide. Criminology 39(30): 517-560.

Moriarty, L.J. (1999). The Conceptualization and Operationalization of the Intervening Dimensions of Social Disorganization. Reading for Research Methods in Criminology and Criminal Justice: Ed. M.L. Dantzker. Boston, BH press.

Nachmias-Frankfurt, C & Nachmias, D. (2000). Research Methods in the Social Sciences. New York: Worth Publishers.

Osgood, D., and Chambers, J. (2000). Social disorganization outside the metropolis: An analysis of rural youth violence. Criminology, 37: 405-426.

Paulsen, D., & Robinson, M. (2004). *Spatial aspects of crime: theory and practice*. Boston: Pearson.

Park, R. E., & Burgess, E. W. (1925). *The City*. Chicago, University of Chicago Press.

Pease, K. (2001). What to do about it? Let's turn off our minds and GIS. In (Ed.) Mapping and Analyzing Crime Data: Lessons from Research and Practice by Alex Hirschfield and Kate Bowers. London. Taylor & Francis Publisher.

Raphael, Steven and Jens Ludwig. (2003). Prison Sentence Enhancements: The case of Project Exile. In Jens Ludwig and Philip J. Cook (eds.), *Evaluating Gun Policy: Effects on Crime and Violence* . Washington, DC: Brookings Institution Press.

Ratcliffe, J. H. and McCullagh, M. J. (1999). Hotbeds of crime and the search for spatial accuracy. Geographical Systems 1(4): 385-398.

Ratcliffe, J. H. (2005). Detecting Spatial Movement of Intra-Region Crime Patterns Over Time. Journal of Quantitative Criminology 21(1): 103-123.

Ratcliffe, J. H. (2002). Burglary reduction and the Myth of Displacement. Australian Institute of Criminology: Trends & Issues in Crime and Criminal Justice, No. 232, July.

Reuland, M. (1997). Information management and crime analysis. Washington, D.C.: Police Executive Research Forum. [On-line], http://www.iaca.net [September 25, 2000].

Ripley, Randall B. and Grace A. Franklin. 1991. "The Nature of Policy and Policy making in the United States, "in *Congress, the Bureaucracy, and Public policy*. California: Brooks/Cole publishing. Pp. 1-25.

Roberts, D.(2005). Virginia Incident-Based Crime Reporting. Criminal Justice Research Center, Research Bulletin. December.

Robinson, M. (2004). *Why crime? An Integrated Systems Theory of Antisocial Behavior*. Upper saddle River, NJ: Prentice Hall.

Robinson, M, (2002). Justice Blind? Ideals and Realities of American Criminal Justice. Upper Saddle River, NJ: Prentice-Hall.

Roh, S. (2005). A Spatial Distribution of Calls for Service in Texas Suburbs: Macro- and Micro- Level Approaches. A Dissertation presented to the Faculty of the College of criminal Justice: Sam Houston State University.

Rose, D.R., and Clear T.R. (1996). Incarceration, social capital, and crime: Implications for social disorganization theory. Retrieved Jan. 10, 2006, from Colombia University, Web site: http://www.jrn.columbia.edu/studentwork/children/examples/Incar-Soc-cap.doc

Rosenbaum, D.P. & Lurigo, A.J. (1994). An inside look at community policing reform: definitions, organizational changes, and evaluation findings. Crime & Delinquency, 40(3), 299-314.

Rosenfeld, R., Fornango, R., and Baumer, E. (2005). Did Ceasefire, Compstat, and Exile Reduce Homicide?. Criminology & Public Policy, 4(3) 415-651

Rossmo, D.K. (2000). Geographic Profiling. CRC Press.

Sampson, R.J. (1986). The effects of urbanization and neighborhood characteristics on criminal victimization. In R.M. Figlio, S. Hakim, and G.F. Rengert (Ed.), Metropolitan Crime Patterns (pp. 3-25). New York: Criminal Justice Press.

Sampson, R. J. (1987). Urban black violence: The effect of male joblessness and family disruption. *American Journal of Sociology*, *93*, 348-382.

Sampson, R. J., & Castellano, T. C (1982). Economic inequality and personal victimization. *British Journal of Criminology*, *22*, 363-385.

Sampson, R. J., & Groves, W. B. (1989). Community structure and crime. *American Journal of Sociology*, *94*(4), 774-802.

Sampson, R.J and Morenoff, J.D. (2004). Spatial (Dis)Advantage and Homicide in Chicago Neighborhoods. In Goodchild, M.F and Janelle, D.G (Ed.), Spatially Integrated Social science. (pp. 145-170). New York: oxford University Press.

Sampson, R.J., Morenoff, J.D., and Rowley, T.G. (2002). Assessing "Neighborhood Effects": Social Process and New Direction in Research. Annnual Review of Sociology. (28): 443-478.

Sastry, N., Pebley, A.R., & Zonta, M. (2002). "Neighborhood Definitions and the Spatial dimension of daily Life in Los Angeles." Labor and Population Program working Paper Series 03-02. RAND and UCLA. Retrieved Jan. 10, 2007, from RAND Cooperation, Web site: http://www.rand.org/pubs/drafts/2006/DRU2400.8.pdf

Schneider, Stephen. (1994). The criminal intelligence function: Toward a Comprehensive and Normative Model. Law Enforcement Intelligence Analyst Digest, 9, (2), 1-26.

Schumacher B.J. and Leitner M. (1999): Spatial crime displacement resulting from large-scale urban renewal programs in the city of Baltimore, MD: A GIS modelling approach. Available: http://www.geovista.psu.edu/sites/geocomp99/Gc99/047/gc_047.htm

Shaw, C. and McKay, H. (1942). Juvenile delinquency and urban areas. University of Chicago Press, Chicago.

Shafritz, J.M., Layne, K.S., and Bairck, P.C. (2004). <u>Context of Public Policy</u>. Classics of Public Policy.

Sherman, L.W. (1990). Police Crackdowns: Initial and Residual Deterrence. <u>Crime and Justice</u>, Vol(12), 1-48.

Shulock, N. 1999. The Parodox of Policy Analysis: If It is Not Used, why Do We Produce So Much of It? *Journal of Policy Analysis and management*, 18(2), pp. 226-244.

Smith, M.R. (2001). Police-Led Crackdowns and cleanups: An evaluation of a crime Control Initiative in Richmond, Virginia. Crime & Delinquency, 47(1): 60-83.

Smith, D. A. and Jarjoura, G. R. (1988). Social structure and criminal victimization. Journal of Research in Crime and Delinquency, 25(1):27–52.

Stallo, M. (1997). Crime analysis: The administrative function. In M. Stallo, & K. Haley, (Eds.), Crime and Punishment in the Lone Star State (pp. 63-76). New York: McGraw-Hill, Inc.

Stark, R. (1987). Deviant places: A theory of the ecology of crime. *Criminology*, Vol(*25)*, 893-910.

Stone, D. (2002). Policy Parodox: The Art of Political Decision Making. Revised Edition. Norton & Company.

Sullenger, T. E. (1950). The social significance of mobility: An Omaha study. *American Journal of Sociology*, Vol(*55)*, 559-564.

Sun, I.Y., Triplett, and Gainey, R.R. (2004). Neighborhood Characteritics and Crime: A test of Sampson and Groves' Model of Social Disorganization. Western Criminology review, 5(1), 1-16.

Taylor, Ralph.(1999). Crime, Grime, Fear, and Decline: A Longitudinal Look. Research in Brief. Washington, DC: National Institute of Justice.

Tolan, P. (2004). Crime Prevention: Focus on Youth. In Crime: Public Policies for Crime Control, ed. James Q. Wilson and Joan Petersilia, 109-127. ICS Press: Oakland, CA.

Tolan, P., and D. Gorman-Smith. (1998). Methods for Evaluating Intervention and Prevention and efforts. In violence against Children in the family and the Community, ed. P.K. Trickett and C. Schellenbach, 439-64. Washington, D.C.: American Psychological Association.

Trochim, W. (2000). The Research Methods Knowledge Base, 2nd Edition. Atomic Dog Publishing, Cincinnati, OH.

Turner, M. G, Gardner, R. H, and O'Neill, R. V. (2001) *Landscape Ecology in Theory and Practice: Pattern and Process.* Springer Verlag: New York.

Veysey, B.M., & Messner, S.F. (1999). Further Testing of Social Disorganization Theory: An Elaboration of Sampson and Groves's "Community Structure and Crime". Journal of Research in Crime and Delinquency, Vol (36), 2.

Warner, B. D. and Pierce, G. L. (1993). Reexamining social disorganization theory using calls to the police as a measure of crime. *Criminology*, 31(4):493–517.

Weimer, David L. and Aidan R. Vining. (2002). "What is Policy Analysis?" In Policy Analysis: Concepts and Practice. Fourth Edition. New Jersey: Prentice Hall. pp. 1-14

Weisburd, D., Lum, C., and Yang, S-M. (2004). Criminal Careers of Places: A Longitudinal Study. Retrevied Jan. 20, 2006, from National Crime and Justice reference Service Web site: http://www.ncjrs.gov/pdffiles1/nij/grants/207824.pdf

Wikipedia. (2007). Available: http://en.wikipedia.org/wiki/Main_Page

Wilson WJ. (1987). The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy. Chicago: Univ. Chicago Press

Wilson, J.Q., & Petersilia, J. (2004). Introduction. In Crime: Public Policies for Crime Control, ed. James Q. Wilson and Joan Petersilia, 1-3. ICS Press: Oakland, CA.

APPENDIX A

GeoLytics: Census 1990 data to Census 2000 areas weighting methodology

The below document is completely extracted from the following web site: http://geolytics.com/USCensus,Census-1990-Long-Form-2000-Boundaries,Data,Methodology,Products.asp

How have characteristics of population and housing changed in the United States over time? What information is available to support this analysis? The Long Form released by the US Census Bureau contains the most detailed set of official US demographics available. In 1990 this set of data is referred to as Summary Tape File 3 (STF3) and in 2000 it is called the Summary File 3 (SF3). There are several issues that arise when you try to compare two sets of data that were collected ten years apart. Direct comparisons between these two sets of data are made more complicated by two factors: 1. changes in the questionnaire design and 2. changes in area boundary definitions.

The first issue, changes in the questionnaire design, has several components: wording of questions that vary, ordering of the questions, categories of questions are dropped and others added. There are also instances of cross-tabulation tables changing, as well as many cross-tabulations that were released in 1990 at the Block Group but only released at the Tract level in 2000. Furthermore, sometimes data for small areas like block groups and tracts were imputed, or taken from like or nearby areas, to protect confidentiality. This also decreases the reliability of the data at smaller levels of geography. Likewise, population under-counting and over-counting may be addressed differently in different census years. These types of issues may be addressed by reviewing the summary information provided by the US Census.

The second obstacle is the changes in geographic definitions. These occur because areas split (1:2), merge (2:1) or both (2:3). The remainder of this paper will discuss how GeoLytics normalized the 1990 Long Form census data to various 2000 geographies. This enables comparisons between 1990 and 2000 Long Form data to be made in standard 2000 geographies. To explain the normalization of 1990 STF3 data to 2000 geographies, we start by weighting and converting 1990 Block Group data to 2000 areas. 1990 Block Group data is used because it is the smallest level of 1990 geography at which the full set of US Census 1990 Long Form data is available. To facilitate the splitting and merging of 1990 Block Groups to 2000 areas, Census Blocks are used. A Census Block is much smaller than a Block Group. There are approximately 30 to 40 Blocks in each Block Group. And unlike previous censuses, Blocks and Block Groups cover 100% of the US in 1990 and 2000.

The 1990 to 2000 Block relations were determined from Tiger/Line 2000, Type 1 and Type 3 records. 85% of the Blocks had a 1:1 relationship, 10% had a 2:1, and 5% had a greater than 2:1. Block splits between 1990 and 2000 were weighted by an analysis of the

1990 streets. To split a Block into parts, the sub-Block areas were weighted according to the 1990 streets relating to each 2000 Block part. The assumption is that local roads indicate where the population lived. 1990 streets were determined using Tiger/Line 1992. Using Tiger 1992 and Tiger 2000 we created a correspondence between 1990 and 2000 Blocks, as well as a weighting value. The weighting value was then used to help split Block demographics for those Blocks that had been split or merged between 1990 and 2000. The file produced by this process is the 1990 to 2000 Block Weighting File (BWF). From this BWF we can roll up the 1990 data to any 2000 geography (tract, zip code, county, etc.).

A final weighting consideration should be noted. The weighting of 1990 Block Group data to 2000 areas has been done as statistically accurately as possible. The 1990 STF3 data is the official Census data and our methodology presents an accurate and comprehensive method to statistically compare 1990 data with 2000 data. However, the converted 1990 data in 2000 boundaries cannot be considered official census data. While a major obstacle to comparing altered geographic areas has been overcome, those areas that have not changed between 1990 and 2000 may contain rounding differences in the weighting process and may not exactly match the official census.

APPENDIX C

DESCRIPTIVE STATISTICS OUTPUTS

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std.	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PR_DIFF_H90	163	8.45	48.16	25.2736	8.45769	.730	.190	.230	.378
PR_DIFF_H99	163	9.12	82.92	49.9956	14.56465	.154	.190	-.332	.378
PR_RENTER_90	163	.00	184.39	50.2215	31.52139	1.321	.190	3.671	.378
PR_RENTER_99	163	.00	100.00	50.3661	25.61029	-.061	.190	-.780	.378
PR_NHWHITE_90	163	.00	100.00	41.1403	34.96690	.355	.190	-1.354	.378
PR_NHWHITE_99	163	.00	100.00	36.0535	34.30207	.618	.190	-1.127	.378
PR_BLACK_90	163	.00	100.00	57.1522	35.74031	-.314	.190	-1.415	.378
PR_BLACK_99	163	.00	100.00	59.2974	34.95835	-.469	.190	-1.275	.378
PR_LATINO_90	163	.00	4.30	.6135	.92598	1.832	.190	3.295	.378
PR_LATINO_99	163	.00	24.33	1.9503	3.45271	3.098	.190	12.903	.378
PR_API_90	163	.00	17.31	.8537	1.83686	5.313	.190	40.618	.378
PR_API_99	163	.00	13.65	1.1113	1.96388	2.825	.190	11.245	.378
PR_OTHER_90	163	.00	3.13	.2817	.49218	2.764	.190	10.742	.378
PR_OTHER_99	163	.00	10.77	1.5875	1.81341	1.680	.190	4.231	.378
RACE_HTRG_90	163	.000	.573	.25507	.188796	.097	.190	-1.516	.378
RACE_HTRG_99	163	.00000	.63429	.2773454	.19608496	.231	.190	-1.334	.378
PR_FDISTRUP_90	163	.00	234.09	32.5266	37.13684	2.144	.190	6.086	.378
PR_FDISTRUP_99	163	.00	64.37	20.7238	15.92938	.624	.190	-.337	.378
PR_POV_BLW_90	163	.00	66.26	18.3567	15.29535	1.181	.190	1.125	.378
PR_POV_BLW_99	163	.00	72.78	21.6286	16.15774	.888	.190	.570	.378
PR_HHLD_PA_90	163	.00	61.87	11.4508	10.99914	1.699	.190	3.518	.378
PR_HHLD_PA_99	163	.00	32.73	5.3007	6.14899	1.659	.190	3.068	.378
PR_UEMP_90	163	.00	18.74	4.2073	3.03868	1.465	.190	4.007	.378
PR_UEMP_99	163	.00	42.03	5.3070	5.32032	3.179	.190	16.857	.378
P_DENSITY_90	163	340.02	21528.83	5550.6177	4111.922	1.501	.190	2.974	.378
P_DENSITY_99	163	325.62	23528.12	5292.8312	3894.460	1.519	.190	3.368	.378
PR_YOUTH_90	163	1.97	81.91	18.0319	11.72851	3.082	.190	12.256	.378
PR_YOUTH_99	163	2.47	99.56	18.2780	13.45280	3.750	.190	18.816	.378
PR_VACANT_90	163	.00	32.15	9.7297	6.84867	1.200	.190	.974	.378
PR_VACANT_99	163	.00	35.32	9.0199	7.27621	1.235	.190	1.880	.378
Valid N (listwise)	163								

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std.	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
H_RATE_90	163	.00	5.07	.5885	1.02878	2.016	.190	3.781	.378
H_RATE_91	163	.00	4.20	.5263	.90378	2.013	.190	3.853	.378
H_RATE_92	163	.00	5.08	.6086	1.04427	2.268	.190	5.653	.378
H_RATE_93	163	.00	4.51	.5876	.99873	1.858	.190	3.105	.378
H_RATE_94	163	.00	7.12	.8255	1.37290	2.261	.190	5.393	.378
H_RATE_95	163	.00	9.93	.6217	1.36860	3.713	.190	17.907	.378
H_RATE_96	163	.00	8.62	.5774	1.09408	3.508	.190	18.892	.378
H_RATE_97	163	.00	9.49	.7927	1.46533	3.098	.190	12.341	.378
H_RATE_98	163	.00	6.33	.5808	1.10973	2.561	.190	7.199	.378
H_RATE_99	163	.00	5.84	.4212	.86270	3.148	.190	13.092	.378
Valid N (listwise)	163								

Correlations

		RES_ MOBILITY_90	RACE_ HTRG_90	PR_ FDISTRUP_ 90	SES_90	P_DENSITY_ 90	PR_ YOUTH_90	PR_ VACANT_90	H_RATE_90
RES_MOBILITY_90	Pearson Correlation	1	.317**	.206**	.156*	.310**	.353**	.262**	.028
	Sig. (2-tailed)		.000	.008	.046	.000	.000	.001	.719
	N	163	163	163	163	163	163	163	163
RACE_HTRG_90	Pearson Correlation	.317**	1	-.080	-.146	-.229**	.084	-.010	-.181*
	Sig. (2-tailed)	.000		.310	.063	.003	.285	.900	.021
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_90	Pearson Correlation	.206**	-.080	1	.795**	.067	.155*	.207**	.553**
	Sig. (2-tailed)	.008	.310		.000	.393	.048	.008	.000
	N	163	163	163	163	163	163	163	163
SES_90	Pearson Correlation	.156*	-.146	.795**	1	.203**	.188*	.381**	.597**
	Sig. (2-tailed)	.046	.063	.000		.009	.016	.000	.000
	N	163	163	163	163	163	163	163	163
P_DENSITY_90	Pearson Correlation	.310**	-.229**	.067	.203**	1	.249**	.080	-.001
	Sig. (2-tailed)	.000	.003	.393	.009		.001	.313	.986
	N	163	163	163	163	163	163	163	163
PR_YOUTH_90	Pearson Correlation	.353**	.084	.155*	.188*	.249**	1	.114	.112
	Sig. (2-tailed)	.000	.285	.048	.016	.001		.149	.155
	N	163	163	163	163	163	163	163	163
PR_VACANT_90	Pearson Correlation	.262**	-.010	.207**	.381**	.080	.114	1	.392**
	Sig. (2-tailed)	.001	.900	.008	.000	.313	.149		.000
	N	163	163	163	163	163	163	163	163
H_RATE_90	Pearson Correlation	.028	-.181*	.553**	.597**	-.001	.112	.392**	1
	Sig. (2-tailed)	.719	.021	.000	.000	.986	.155	.000	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RES_ MOBILITY_91	RACE_ HTRG_91	PR_ FDISTRUP_ 91	SES_91	P_DENSITY_ 91	PR_ YOUTH_91	PR_ VACANT_91	H_RATE_91
RES_MOBILITY_91	Pearson Correlation	1	.291**	.334**	.302**	.354**	.450**	.316**	.082
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.295
	N	163	163	163	163	163	163	163	163
RACE_HTRG_91	Pearson Correlation	.291**	1	-.090	-.156*	-.225**	.092	-.013	-.153
	Sig. (2-tailed)	.000		.254	.046	.004	.242	.871	.052
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_91	Pearson Correlation	.334**	-.090	1	.805**	.066	.161*	.230**	.319**
	Sig. (2-tailed)	.000	.254		.000	.400	.040	.003	.000
	N	163	163	163	163	163	163	163	163
SES_91	Pearson Correlation	.302**	-.156*	.805**	1	.200*	.219**	.404**	.350**
	Sig. (2-tailed)	.000	.046	.000		.010	.005	.000	.000
	N	163	163	163	163	163	163	163	163
P_DENSITY_91	Pearson Correlation	.354**	-.225**	.066	.200*	1	.255**	.084	.060
	Sig. (2-tailed)	.000	.004	.400	.010		.001	.289	.445
	N	163	163	163	163	163	163	163	163
PR_YOUTH_91	Pearson Correlation	.450**	.092	.161*	.219**	.255**	1	.122	.090
	Sig. (2-tailed)	.000	.242	.040	.005	.001		.122	.251
	N	163	163	163	163	163	163	163	163
PR_VACANT_91	Pearson Correlation	.316**	-.013	.230**	.404**	.084	.122	1	.213**
	Sig. (2-tailed)	.000	.871	.003	.000	.289	.122		.006
	N	163	163	163	163	163	163	163	163
H_RATE_91	Pearson Correlation	.082	-.153	.319**	.350**	.060	.090	.213**	1
	Sig. (2-tailed)	.295	.052	.000	.000	.445	.251	.006	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RES_ MOBILITY_92	RACE_ HTRG_92	PR_ FDISTRUP_ 92	SES_92	P_DENSITY_ 92	PR_ YOUTH_92	PR_ VACANT_92	H_RATE_92
RES_MOBILITY_92	Pearson Correlation	1	.306**	.328**	.302**	.361**	.452**	.311**	.111
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.157
	N	163	163	163	163	163	163	163	163
RACE_HTRG_92	Pearson Correlation	.306**	1	-.099	-.168*	-.218**	.100	-.017	-.125
	Sig. (2-tailed)	.000		.210	.032	.005	.205	.830	.111
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_92	Pearson Correlation	.328**	-.099	1	.814**	.065	.166*	.253**	.419**
	Sig. (2-tailed)	.000	.210		.000	.412	.034	.001	.000
	N	163	163	163	163	163	163	163	163
SES_92	Pearson Correlation	.302**	-.168*	.814**	1	.197*	.251**	.425**	.483**
	Sig. (2-tailed)	.000	.032	.000		.012	.001	.000	.000
	N	163	163	163	163	163	163	163	163
P_DENSITY_92	Pearson Correlation	.361**	-.218**	.065	.197*	1	.261**	.086	-.035
	Sig. (2-tailed)	.000	.005	.412	.012		.001	.276	.659
	N	163	163	163	163	163	163	163	163
PR_YOUTH_92	Pearson Correlation	.452**	.100	.166*	.251**	.261**	1	.129	-.007
	Sig. (2-tailed)	.000	.205	.034	.001	.001		.100	.930
	N	163	163	163	163	163	163	163	163
PR_VACANT_92	Pearson Correlation	.311**	-.017	.253**	.425**	.086	.129	1	.450**
	Sig. (2-tailed)	.000	.830	.001	.000	.276	.100		.000
	N	163	163	163	163	163	163	163	163
H_RATE_92	Pearson Correlation	.111	-.125	.419**	.483**	-.035	-.007	.450**	1
	Sig. (2-tailed)	.157	.111	.000	.000	.659	.930	.000	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RES_ MOBILITY_93	RACE_ HTRG_93	PR_ FDISTRUP_ 93	SES_93	P_DENSITY_ 93	PR_ YOUTH_93	PR_ VACANT_93	H_RATE_93
RES_MOBILITY_93	Pearson Correlation	1	.318**	.321**	.303**	.370**	.454**	.303**	.181*
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.020
	N	163	163	163	163	163	163	163	163
RACE_HTRG_93	Pearson Correlation	.318**	1	-.107	-.180*	-.209**	.107	-.023	-.030
	Sig. (2-tailed)	.000		.176	.022	.007	.174	.775	.704
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_93	Pearson Correlation	.321**	-.107	1	.822**	.062	.171*	.275**	.355**
	Sig. (2-tailed)	.000	.176		.000	.429	.029	.000	.000
	N	163	163	163	163	163	163	163	163
SES_93	Pearson Correlation	.303**	-.180*	.822**	1	.195*	.279**	.441**	.489**
	Sig. (2-tailed)	.000	.022	.000		.013	.000	.000	.000
	N	163	163	163	163	163	163	163	163
P_DENSITY_93	Pearson Correlation	.370**	-.209**	.062	.195*	1	.265**	.086	.018
	Sig. (2-tailed)	.000	.007	.429	.013		.001	.272	.824
	N	163	163	163	163	163	163	163	163
PR_YOUTH_93	Pearson Correlation	.454**	.107	.171*	.279**	.265**	1	.136	.165*
	Sig. (2-tailed)	.000	.174	.029	.000	.001		.082	.036
	N	163	163	163	163	163	163	163	163
PR_VACANT_93	Pearson Correlation	.303**	-.023	.275**	.441**	.086	.136	1	.492**
	Sig. (2-tailed)	.000	.775	.000	.000	.272	.082		.000
	N	163	163	163	163	163	163	163	163
H_RATE_93	Pearson Correlation	.181*	-.030	.355**	.489**	.018	.165*	.492**	1
	Sig. (2-tailed)	.020	.704	.000	.000	.824	.036	.000	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RES_ MOBILITY_94	RACE_ HTRG_94	PR_ FDISTRUP_ 94	SES_94	P_DENSITY_ 94	PR_ YOUTH_94	PR_ VACANT_94	H_RATE_94
RES_MOBILITY_94	Pearson Correlation	1	.326**	.315**	.304**	.381**	.453**	.292**	.089
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.259
	N	163	163	163	163	163	163	163	163
RACE_HTRG_94	Pearson Correlation	.326**	1	-.114	-.192*	-.198*	.113	-.030	-.104
	Sig. (2-tailed)	.000		.148	.014	.011	.151	.708	.185
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_94	Pearson Correlation	.315**	-.114	1	.828**	.059	.174*	.295**	.386**
	Sig. (2-tailed)	.000	.148		.000	.451	.026	.000	.000
	N	163	163	163	163	163	163	163	163
SES_94	Pearson Correlation	.304**	-.192*	.828**	1	.192*	.303**	.454**	.499**
	Sig. (2-tailed)	.000	.014	.000		.014	.000	.000	.000
	N	163	163	163	163	163	163	163	163
P_DENSITY_94	Pearson Correlation	.381**	-.198*	.059	.192*	1	.269**	.085	.057
	Sig. (2-tailed)	.000	.011	.451	.014		.001	.278	.472
	N	163	163	163	163	163	163	163	163
PR_YOUTH_94	Pearson Correlation	.453**	.113	.174*	.303**	.269**	1	.142	.056
	Sig. (2-tailed)	.000	.151	.026	.000	.001		.070	.477
	N	163	163	163	163	163	163	163	163
PR_VACANT_94	Pearson Correlation	.292**	-.030	.295**	.454**	.085	.142	1	.320**
	Sig. (2-tailed)	.000	.708	.000	.000	.278	.070		.000
	N	163	163	163	163	163	163	163	163
H_RATE_94	Pearson Correlation	.089	-.104	.386**	.499**	.057	.056	.320**	1
	Sig. (2-tailed)	.259	.185	.000	.000	.472	.477	.000	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RES_ MOBILITY_95	RACE_ HTRG_95	PR_ FDISTRUP_ 95	SES_95	P_DENSITY_ 95	PR_ YOUTH_95	PR_ VACANT_95	H_RATE_95
RES_MOBILITY_95	Pearson Correlation	1	.330**	.308**	.305**	.393**	.452**	.280**	.170*
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.030
	N	163	163	163	163	163	163	163	163
RACE_HTRG_95	Pearson Correlation	.330**	1	-.120	-.203**	-.185*	.118	-.038	-.008
	Sig. (2-tailed)	.000		.126	.009	.018	.133	.630	.914
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_95	Pearson Correlation	.308**	-.120	1	.830**	.056	.177*	.311**	.513**
	Sig. (2-tailed)	.000	.126		.000	.476	.024	.000	.000
	N	163	163	163	163	163	163	163	163
SES_95	Pearson Correlation	.305**	-.203**	.830**	1	.190*	.320**	.462**	.443**
	Sig. (2-tailed)	.000	.009	.000		.015	.000	.000	.000
	N	163	163	163	163	163	163	163	163
P_DENSITY_95	Pearson Correlation	.393**	-.185*	.056	.190*	1	.271**	.083	-.101
	Sig. (2-tailed)	.000	.018	.476	.015		.000	.291	.200
	N	163	163	163	163	163	163	163	163
PR_YOUTH_95	Pearson Correlation	.452**	.118	.177*	.320**	.271**	1	.147	.057
	Sig. (2-tailed)	.000	.133	.024	.000	.000		.061	.470
	N	163	163	163	163	163	163	163	163
PR_VACANT_95	Pearson Correlation	.280**	-.038	.311**	.462**	.083	.147	1	.345**
	Sig. (2-tailed)	.000	.630	.000	.000	.291	.061		.000
	N	163	163	163	163	163	163	163	163
H_RATE_95	Pearson Correlation	.170*	-.008	.513**	.443**	-.101	.057	.345**	1
	Sig. (2-tailed)	.030	.914	.000	.000	.200	.470	.000	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RES_ MOBILITY_96	RACE_ HTRG_96	PR_ FDISTRUP_ 96	SES_96	P_DENSITY_ 96	PR_ YOUTH_96	PR_ VACANT_96	H_RATE_96
RES_MOBILITY_96	Pearson Correlation	1	.330**	.301**	.307**	.404**	.449**	.268**	.120
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.001	.126
	N	163	163	163	163	163	163	163	163
RACE_HTRG_96	Pearson Correlation	.330**	1	-.126	-.214**	-.171*	.122	-.048	-.155*
	Sig. (2-tailed)	.000		.109	.006	.029	.120	.544	.048
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_96	Pearson Correlation	.301**	-.126	1	.827**	.053	.178*	.320**	.307**
	Sig. (2-tailed)	.000	.109		.000	.500	.023	.000	.000
	N	163	163	163	163	163	163	163	163
SES_96	Pearson Correlation	.307**	-.214**	.827**	1	.187*	.332**	.464**	.369**
	Sig. (2-tailed)	.000	.006	.000		.017	.000	.000	.000
	N	163	163	163	163	163	163	163	163
P_DENSITY_96	Pearson Correlation	.404**	-.171*	.053	.187*	1	.272**	.080	.127
	Sig. (2-tailed)	.000	.029	.500	.017		.000	.311	.105
	N	163	163	163	163	163	163	163	163
PR_YOUTH_96	Pearson Correlation	.449**	.122	.178*	.332**	.272**	1	.149	.080
	Sig. (2-tailed)	.000	.120	.023	.000	.000		.057	.307
	N	163	163	163	163	163	163	163	163
PR_VACANT_96	Pearson Correlation	.268**	-.048	.320**	.464**	.080	.149	1	.299**
	Sig. (2-tailed)	.001	.544	.000	.000	.311	.057		.000
	N	163	163	163	163	163	163	163	163
H_RATE_96	Pearson Correlation	.120	-.155*	.307**	.369**	.127	.080	.299**	1
	Sig. (2-tailed)	.126	.048	.000	.000	.105	.307	.000	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RES_ MOBILITY_97	RACE_ HTRG_97	PR_ FDISTRUP_ 97	SES_97	P_DENSITY_ 97	PR_ YOUTH_97	PR_ VACANT_97	H_RATE_97
RES_MOBILITY_97	Pearson Correlation	1	.326**	.295**	.311**	.415**	.443**	.256**	.037
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.001	.636
	N	163	163	163	163	163	163	163	163
RACE_HTRG_97	Pearson Correlation	.326**	1	-.130	-.221**	-.155*	.125	-.059	-.254**
	Sig. (2-tailed)	.000		.098	.004	.049	.112	.454	.001
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_97	Pearson Correlation	.295**	-.130	1	.816**	.051	.175*	.320**	.321**
	Sig. (2-tailed)	.000	.098		.000	.514	.026	.000	.000
	N	163	163	163	163	163	163	163	163
SES_97	Pearson Correlation	.311**	-.221**	.816**	1	.185*	.339**	.460**	.374**
	Sig. (2-tailed)	.000	.004	.000		.018	.000	.000	.000
	N	163	163	163	163	163	163	163	163
P_DENSITY_97	Pearson Correlation	.415**	-.155*	.051	.185*	1	.272**	.076	-.062
	Sig. (2-tailed)	.000	.049	.514	.018		.000	.333	.433
	N	163	163	163	163	163	163	163	163
PR_YOUTH_97	Pearson Correlation	.443**	.125	.175*	.339**	.272**	1	.148	.002
	Sig. (2-tailed)	.000	.112	.026	.000	.000		.060	.982
	N	163	163	163	163	163	163	163	163
PR_VACANT_97	Pearson Correlation	.256**	-.059	.320**	.460**	.076	.148	1	.320**
	Sig. (2-tailed)	.001	.454	.000	.000	.333	.060		.000
	N	163	163	163	163	163	163	163	163
H_RATE_97	Pearson Correlation	.037	-.254**	.321**	.374**	-.062	.002	.320**	1
	Sig. (2-tailed)	.636	.001	.000	.000	.433	.982	.000	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RES_ MOBILITY_98	RACE_ HTRG_98	PR_ FDISTRUP_ 98	SES_98	P_DENSITY_ 98	PR_ YOUTH_98	PR_ VACANT_98	H_RATE_98
RES_MOBILITY_98	Pearson Correlation	1	.318**	.288**	.319**	.422**	.436**	.246**	.091
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.002	.248
	N	163	163	163	163	163	163	163	163
RACE_HTRG_98	Pearson Correlation	.318**	1	-.131	-.226**	-.137	.126	-.072	-.167*
	Sig. (2-tailed)	.000		.095	.004	.081	.110	.358	.033
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_98	Pearson Correlation	.288**	-.131	1	.791**	.054	.164*	.308**	.308**
	Sig. (2-tailed)	.000	.095		.000	.492	.036	.000	.000
	N	163	163	163	163	163	163	163	163
SES_98	Pearson Correlation	.319**	-.226**	.791**	1	.187*	.338**	.448**	.315**
	Sig. (2-tailed)	.000	.004	.000		.017	.000	.000	.000
	N	163	163	163	163	163	163	163	163
P_DENSITY_98	Pearson Correlation	.422**	-.137	.054	.187*	1	.269**	.074	-.022
	Sig. (2-tailed)	.000	.081	.492	.017		.001	.347	.782
	N	163	163	163	163	163	163	163	163
PR_YOUTH_98	Pearson Correlation	.436**	.126	.164*	.338**	.269**	1	.137	.047
	Sig. (2-tailed)	.000	.110	.036	.000	.001		.081	.547
	N	163	163	163	163	163	163	163	163
PR_VACANT_98	Pearson Correlation	.246**	-.072	.308**	.448**	.074	.137	1	.388**
	Sig. (2-tailed)	.002	.358	.000	.000	.347	.081		.000
	N	163	163	163	163	163	163	163	163
H_RATE_98	Pearson Correlation	.091	-.167*	.308**	.315**	-.022	.047	.388**	1
	Sig. (2-tailed)	.248	.033	.000	.000	.782	.547	.000	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RES_ MOBILITY_99	RACE_ HTRG_99	PR_ FDISTRUP_ 99	SES_99	P_DENSITY_ 99	PR_ YOUTH_99	PR_ VACANT_99	H_RATE_99
RES_MOBILITY_99	Pearson Correlation	1	.306**	.278**	.322**	.421**	.427**	.202**	.061
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.010	.441
	N	163	163	163	163	163	163	163	163
RACE_HTRG_99	Pearson Correlation	.306**	1	-.118	-.230**	-.118	.125	-.117	-.171*
	Sig. (2-tailed)	.000		.132	.003	.133	.113	.136	.029
	N	163	163	163	163	163	163	163	163
PR_FDISTRUP_99	Pearson Correlation	.278**	-.118	1	.747**	.077	.128	.315**	.131
	Sig. (2-tailed)	.000	.132		.000	.328	.104	.000	.097
	N	163	163	163	163	163	163	163	163
SES_99	Pearson Correlation	.322**	-.230**	.747**	1	.202**	.300**	.434**	.255**
	Sig. (2-tailed)	.000	.003	.000		.010	.000	.000	.001
	N	163	163	163	163	163	163	163	163
P_DENSITY_99	Pearson Correlation	.421**	-.118	.077	.202**	1	.265**	.092	.017
	Sig. (2-tailed)	.000	.133	.328	.010		.001	.242	.827
	N	163	163	163	163	163	163	163	163
PR_YOUTH_99	Pearson Correlation	.427**	.125	.128	.300**	.265**	1	.002	-.024
	Sig. (2-tailed)	.000	.113	.104	.000	.001		.985	.757
	N	163	163	163	163	163	163	163	163
PR_VACANT_99	Pearson Correlation	.202**	-.117	.315**	.434**	.092	.002	1	.272**
	Sig. (2-tailed)	.010	.136	.000	.000	.242	.985		.000
	N	163	163	163	163	163	163	163	163
H_RATE_99	Pearson Correlation	.061	-.171*	.131	.255**	.017	-.024	.272**	1
	Sig. (2-tailed)	.441	.029	.097	.001	.827	.757	.000	
	N	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

APPENDIX C

BINARY LOGISTICS REGRESSION OUTPUTS

YEAR 1990

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	56.377	7	.000
	Block	56.377	7	.000
	Model	56.377	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	155.843[a]	.292	.402

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Classification Table[a]

			Predicted		
			YES OR NO		Percentage Correct
	Observed		.00	1.00	
Step 1	YES OR NO	.00	92	13	87.6
		1.00	25	33	56.9
	Overall Percentage				76.7

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_90	-.305	.270	1.278	1	.258	.737
	RACE_HTRG_90	-.365	1.254	.085	1	.771	.694
	PR_FDISTRUP_90	.023	.010	5.093	1	.024	1.023
	SES_90	.392	.379	1.070	1	.301	1.480
	P_DENSITY_90	.000	.000	2.676	1	.102	1.000
	PR_YOUTH_90	.004	.018	.054	1	.817	1.004
	PR_VACANT_90	.094	.035	7.477	1	.006	1.099
	Constant	-2.915	.932	9.784	1	.002	.054

a. Variable(s) entered on step 1: RES_MOBILITY_90, RACE_HTRG_90, PR_FDISTRUP_90, SES_90, P_DENSITY_90, PR_YOUTH_90, PR_VACANT_90.

YEAR 1991

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	20.879	7	.004
	Block	20.879	7	.004
	Model	20.879	7	.004

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	192.501[a]	.120	.165

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted DUMMY_HOM_91 .00	Predicted DUMMY_HOM_91 1.00	Percentage Correct
Step 1	DUMMY_HOM_91	.00	93	11	89.4
		1.00	38	21	35.6
	Overall Percentage				69.9

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_91	.168	.249	.453	1	.501	1.183
	RACE_HTRG_91	-.969	1.088	.792	1	.374	.380
	PR_FDISTRUP_91	.002	.009	.033	1	.856	1.002
	SES_91	.555	.346	2.571	1	.109	1.742
	P_DENSITY_91	.000	.000	.025	1	.874	1.000
	PR_YOUTH_91	.009	.016	.300	1	.584	1.009
	PR_VACANT_91	.014	.030	.231	1	.631	1.015
	Constant	-.767	.839	.836	1	.361	.464

a. Variable(s) entered on step 1: RES_MOBILITY_91, RACE_HTRG_91, PR_FDISTRUP_91, SES_91, P_DENSITY_91, PR_YOUTH_91, PR_VACANT_91.

YEAR 1992

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	40.022	7	.000
	Block	40.022	7	.000
	Model	40.022	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	176.521[a]	.218	.296

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted DUMMY_HOM_92 .00	Predicted DUMMY_HOM_92 1.00	Percentage Correct
Step 1	DUMMY_HOM_92	.00	88	13	87.1
		1.00	29	33	53.2
	Overall Percentage				74.2

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_92	-.055	.267	.043	1	.836	.946
	RACE_HTRG_92	-.432	1.179	.134	1	.714	.650
	PR_FDISTRUP_92	.014	.012	1.357	1	.244	1.014
	SES_92	.643	.395	2.645	1	.104	1.902
	P_DENSITY_92	.000	.000	.004	1	.953	1.000
	PR_YOUTH_92	-.008	.018	.215	1	.643	.992
	PR_VACANT_92	.059	.034	2.918	1	.088	1.060
	Constant	-1.272	.953	1.781	1	.182	.280

a. Variable(s) entered on step 1: RES_MOBILITY_92, RACE_HTRG_92, PR_FDISTRUP_92, SES_92, P_DENSITY_92, PR_YOUTH_92, PR_VACANT_92.

YEAR 1993

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	49.381	7	.000
	Block	49.381	7	.000
	Model	49.381	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	160.357[a]	.261	.361

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted DUMMY_HOM_93 .00	Predicted DUMMY_HOM_93 1.00	Percentage Correct
Step 1	DUMMY_HOM_93	.00	94	13	87.9
		1.00	24	32	57.1
	Overall Percentage				77.3

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_93	-.102	.286	.128	1	.720	.903
	RACE_HTRG_93	2.839	1.335	4.524	1	.033	17.095
	PR_FDISTRUP_93	.008	.013	.379	1	.538	1.008
	SES_93	.937	.414	5.120	1	.024	2.553
	P_DENSITY_93	.000	.000	.163	1	.687	1.000
	PR_YOUTH_93	-.006	.021	.074	1	.786	.994
	PR_VACANT_93	.098	.037	7.168	1	.007	1.103
	Constant	-2.569	1.064	5.828	1	.016	.077

a. Variable(s) entered on step 1: RES_MOBILITY_93, RACE_HTRG_93, PR_FDISTRUP_93, SES_93, P_DENSITY_93, PR_YOUTH_93, PR_VACANT_93.

YEAR 1994

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	44.536	6	.000
	Block	44.536	6	.000
	Model	44.536	6	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	165.202[a]	.239	.330

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted DUMMY_HOM_93 .00	Predicted DUMMY_HOM_93 1.00	Percentage Correct
Step 1	DUMMY_HOM_93	.00	92	15	86.0
		1.00	27	29	51.8
	Overall Percentage				74.2

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_93	.194	.245	.627	1	.429	1.214
	PR_FDISTRUP_93	.005	.013	.169	1	.681	1.005
	SES_93	.789	.404	3.822	1	.051	2.201
	P_DENSITY_93	.000	.000	1.836	1	.175	1.000
	PR_YOUTH_93	-.003	.019	.018	1	.894	.997
	PR_VACANT_93	.084	.035	5.759	1	.016	1.088
	Constant	-1.299	.848	2.342	1	.126	.273

a. Variable(s) entered on step 1: RES_MOBILITY_93, PR_FDISTRUP_93, SES_93, P_DENSITY_93, PR_YOUTH_93, PR_VACANT_93.

YEAR 1994

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	122.044[a]	.209	.301

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	30.053	7	.000
	Block	30.053	7	.000
	Model	30.053	7	.000

Classification Table[a]

			Predicted		
			DUMMY_HOM_94		Percentage Correct
	Observed		.00	1.00	
Step 1	DUMMY_HOM_94	.00	86	6	93.5
		1.00	25	11	30.6
	Overall Percentage				75.8

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_94	-.359	.336	1.142	1	.285	.698
	RACE_HTRG_94	1.043	1.518	.472	1	.492	2.838
	PR_FDISTRUP_94	-.013	.015	.786	1	.375	.987
	SES_94	.818	.538	2.310	1	.129	2.266
	P_DENSITY_94	.000	.000	4.164	1	.041	1.000
	PR_YOUTH_94	-.020	.025	.607	1	.436	.981
	PR_VACANT_94	.126	.044	8.114	1	.004	1.134
	Constant	-2.515	1.209	4.325	1	.038	.081

a. Variable(s) entered on step 1: RES_MOBILITY_94, RACE_HTRG_94, PR_FDISTRUP_94, SES_94, P_DENSITY_94, PR_YOUTH_94, PR_VACANT_94.

YEAR 1995

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	34.066	7	.000
	Block	34.066	7	.000
	Model	34.066	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	171.540[a]	.189	.263

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Classification Table[a]

	Observed		Predicted DUMMY_HOM_95 .00	Predicted DUMMY_HOM_95 1.00	Percentage Correct
Step 1	DUMMY_HOM_95	.00	98	12	89.1
		1.00	32	21	39.6
	Overall Percentage				73.0

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_95	.302	.271	1.242	1	.265	1.352
	RACE_HTRG_95	.683	1.212	.318	1	.573	1.981
	PR_FDISTRUP_95	.030	.015	3.957	1	.047	1.030
	SES_95	.188	.404	.218	1	.640	1.207
	P_DENSITY_95	.000	.000	.393	1	.531	1.000
	PR_YOUTH_95	-.001	.018	.006	1	.938	.999
	PR_VACANT_95	.032	.033	.961	1	.327	1.033
	Constant	-1.931	.974	3.927	1	.048	.145

a. Variable(s) entered on step 1: RES_MOBILITY_95, RACE_HTRG_95, PR_FDISTRUP_95, SES_95, P_DENSITY_95, PR_YOUTH_95, PR_VACANT_95.

YEAR 1996

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	28.522	7	.000
	Block	28.522	7	.000
	Model	28.522	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	184.858[a]	.161	.220

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted DUMMY_HOM_96 .00	Predicted DUMMY_HOM_96 1.00	Percentage Correct
Step 1	DUMMY_HOM_96	.00	89	15	85.6
		1.00	33	26	44.1
	Overall Percentage				70.6

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_96	.200	.258	.604	1	.437	1.222
	RACE_HTRG_96	-.449	1.165	.149	1	.700	.638
	PR_FDISTRUP_96	.005	.014	.139	1	.710	1.005
	SES_96	.521	.375	1.932	1	.165	1.684
	P_DENSITY_96	.000	.000	2.122	1	.145	1.000
	PR_YOUTH_96	-.012	.018	.416	1	.519	.989
	PR_VACANT_96	.043	.031	1.909	1	.167	1.044
	Constant	-1.290	.881	2.141	1	.143	.275

a. Variable(s) entered on step 1: RES_MOBILITY_96, RACE_HTRG_96, PR_FDISTRUP_96, SES_96, P_DENSITY_96, PR_YOUTH_96, PR_VACANT_96.

YEAR 1997

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	32.367	7	.000
	Block	32.367	7	.000
	Model	32.367	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	188.412[a]	.180	.243

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

	Observed		Predicted		
			DUMMY_HOM_97		Percentage Correct
			.00	1.00	
Step 1	DUMMY_HOM_97	.00	79	17	82.3
		1.00	36	31	46.3
	Overall Percentage				67.5

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_97	.254	.249	1.037	1	.309	1.289
	RACE_HTRG_97	-1.159	1.126	1.060	1	.303	.314
	PR_FDISTRUP_97	.009	.016	.356	1	.551	1.009
	SES_97	.693	.374	3.428	1	.064	1.999
	P_DENSITY_97	.000	.000	.306	1	.580	1.000
	PR_YOUTH_97	-.015	.018	.717	1	.397	.985
	PR_VACANT_97	.015	.031	.235	1	.628	1.015
	Constant	-.314	.855	.135	1	.713	.730

a. Variable(s) entered on step 1: RES_MOBILITY_97, RACE_HTRG_97, PR_FDISTRUP_97, SES_97, P_DENSITY_97, PR_YOUTH_97, PR_VACANT_97.

YEAR 1998

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	31.100	7	.000
	Block	31.100	7	.000
	Model	31.100	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	178.638[a]	.174	.240

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

			Predicted		
			DUMMY_HOM_98		Percentage Correct
	Observed		.00	1.00	
Step 1	DUMMY_HOM_98	.00	93	14	86.9
		1.00	33	23	41.1
	Overall Percentage				71.2

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_98	.156	.260	.360	1	.549	1.169
	RACE_HTRG_98	-.868	1.171	.549	1	.459	.420
	PR_FDISTRUP_98	.018	.016	1.260	1	.262	1.019
	SES_98	.355	.343	1.069	1	.301	1.426
	P_DENSITY_98	.000	.000	.015	1	.903	1.000
	PR_YOUTH_98	-.009	.018	.251	1	.616	.991
	PR_VACANT_98	.065	.030	4.745	1	.029	1.067
	Constant	-1.407	.852	2.728	1	.099	.245

a. Variable(s) entered on step 1: RES_MOBILITY_98, RACE_HTRG_98, PR_FDISTRUP_98, SES_98, P_DENSITY_98, PR_YOUTH_98, PR_VACANT_98.

YEAR 1999

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	25.471	8	.001
	Block	25.471	8	.001
	Model	25.471	8	.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	173.840[a]	.145	.205

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

			Predicted		
			YES OR NO		Percentage Correct
	Observed		.00	1.00	
Step 1	YES OR NO	.00	103	11	90.4
		1.00	31	18	36.7
	Overall Percentage				74.2

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY_99	.316	.264	1.430	1	.232	1.371
	RACE_HTRG_99	-1.178	1.173	1.009	1	.315	.308
	PR_FDISTRUP_99	.010	.017	.378	1	.539	1.011
	SES_99	.488	.318	2.352	1	.125	1.629
	P_DENSITY_99	.000	.000	.166	1	.683	1.000
	PR_YOUTH_99	-.014	.020	.455	1	.500	.986
	PR_VACANT_99	.024	.033	.557	1	.456	1.025
	BLITZ_99	.385	.675	.325	1	.568	1.469
	Constant	-.758	.809	.877	1	.349	.469

a. Variable(s) entered on step 1: RES_MOBILITY_99, RACE_HTRG_99, PR_FDISTRUP_99, SES_99, P_DENSITY_99, PR_YOUTH_99, PR_VACANT_99, BLITZ_99.

YEAR ALL

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	296.222	8	.000
	Block	296.222	8	.000
	Model	296.222	8	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1765.080[a]	.169	.234

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted YES OR NO .00	Predicted YES OR NO 1.00	Percentage Correct
Step 1	YES OR NO	.00	902	138	86.7
		1.00	324	231	41.6
	Overall Percentage				71.0

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RES_MOBILITY	.076	.081	.890	1	.346	1.079
	RACE_HTRG	-.218	.369	.351	1	.554	.804
	PR_FDISTRUPT	.010	.004	7.462	1	.006	1.010
	SES	.547	.108	25.532	1	.000	1.728
	P_DENSITY	.000	.000	1.937	1	.164	1.000
	PR_YOUTH	-.006	.006	1.123	1	.289	.994
	PR_VACANT	.052	.010	27.049	1	.000	1.053
	DUMMY_BBLOOM	-.085	.507	.028	1	.867	.919
	Constant	-1.426	.267	28.409	1	.000	.240

a. Variable(s) entered on step 1: RES_MOBILITY, RACE_HTRG, PR_FDISTRUPT, SES, P_DENSITY, PR_YOUTH, PR_VACANT, DUMMY_BBLOOM.

APPENDIX D

MULTINOMIAL LOGISTICS REGRESSION OUTPUTS

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.90@99	1.00	97	59.5%
	2.00	40	24.5%
	3.00	26	16.0%
NEIGHBORHOODS IN BLOOM AREA	1	18	11.0%
	2	36	22.1%
	3	109	66.9%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	308.537			
Final	271.141	37.396	18	.005

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	325.295	306	.214
Deviance	271.141	306	.925

Pseudo R-Square

Cox and Snell	.205
Nagelkerke	.241
McFadden	.121

Parameter Estimates

CAT_CH_HOMICIDE.90@99[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2.00	Intercept	-1.656	.294	31.778	1	.000			
	CH_RES_MOBILITY_90@99	.231	.380	.368	1	.544	1.259	.598	2.654
	CH_RACE_HTRG_90@99	.113	2.230	.003	1	.960	1.119	.014	88.493
	CH_PR_FDISTRUP_90@99	-.016	.008	3.833	1	.050	.984	.968	1.000
	CH_SES_90@99	-.212	.305	.482	1	.487	.809	.445	1.472
	CH_P_DENSITY_90@99	.000	.000	.063	1	.801	1.000	1.000	1.000
	CH_PR_YOUTH_90@99	.034	.036	.883	1	.347	1.034	.964	1.109
	CH_PR_VACANT_90@99	-.003	.034	.011	1	.918	.997	.933	1.064
	[BBLOOM_99=1]	1.433	.650	4.862	1	.027	4.192	1.173	14.986
	[BBLOOM_99=2]	1.177	.507	5.392	1	.020	3.245	1.201	8.766
	[BBLOOM_99=3]	0[b]	.	.	0	.	.	.	.
3.00	Intercept	-1.639	.308	28.252	1	.000			
	CH_RES_MOBILITY_90@99	.987	.521	3.591	1	.058	2.683	.967	7.443
	CH_RACE_HTRG_90@99	.022	2.503	.000	1	.993	1.022	.008	138.106
	CH_PR_FDISTRUP_90@99	.020	.014	2.048	1	.152	1.020	.993	1.048
	CH_SES_90@99	.069	.359	.037	1	.847	1.072	.530	2.168
	CH_P_DENSITY_90@99	.000	.000	.034	1	.853	1.000	1.000	1.000
	CH_PR_YOUTH_90@99	-.052	.039	1.784	1	.182	.950	.880	1.024
	CH_PR_VACANT_90@99	-.008	.040	.036	1	.850	.992	.917	1.074
	[BBLOOM_99=1]	1.292	.718	3.242	1	.072	3.641	.892	14.868
	[BBLOOM_99=2]	.990	.611	2.626	1	.105	2.690	.813	8.905
	[BBLOOM_99=3]	0[b]	.	.	0	.	.	.	.

a. The reference category is: 1.00.

b. This parameter is set to zero because it is redundant.

The difference model between 1990 and 1994

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.90@94	1.00	89	54.6%
	2.00	31	19.0%
	3.00	43	26.4%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	325.215			
Final	299.166	26.049	14	.026

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	332.428	310	.182
Deviance	299.166	310	.660

Pseudo R-Square

Cox and Snell	.148
Nagelkerke	.171
McFadden	.080

Parameter Estimates

CAT_CH_ HOMICIDE.90@94[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2.00	Intercept	-1.472	.286	26.504	1	.000			
	CH_RES_MOBILITY_ 90@94	1.518	.774	3.853	1	.050	4.565	1.002	20.793
	CH_RACE_HTRG_ 90@94	-2.129	5.355	.158	1	.691	.119	3.29E-006	4300.905
	CH_PR_FDISTRUP_ 90@94	-.067	.023	8.726	1	.003	.935	.895	.978
	CH_SES_90@94	-.225	.707	.101	1	.750	.798	.200	3.192
	CH_P_DENSITY_90@94	.000	.000	.001	1	.978	1.000	.999	1.001
	CH_PR_YOUTH_90@94	.045	.087	.268	1	.605	1.046	.882	1.241
	CH_PR_VACANT_90@94	.007	.095	.005	1	.942	1.007	.836	1.213
3.00	Intercept	-.897	.232	15.018	1	.000			
	CH_RES_MOBILITY_ 90@94	-.152	.585	.068	1	.795	.859	.273	2.703
	CH_RACE_HTRG_ 90@94	-1.132	4.507	.063	1	.802	.322	4.70E-005	2211.766
	CH_PR_FDISTRUP_ 90@94	-.037	.022	2.941	1	.086	.964	.924	1.005
	CH_SES_90@94	-.119	.642	.034	1	.853	.888	.252	3.124
	CH_P_DENSITY_90@94	.000	.000	2.015	1	.156	1.000	.999	1.000
	CH_PR_YOUTH_90@94	.047	.068	.479	1	.489	1.048	.917	1.198
	CH_PR_VACANT_90@94	.128	.083	2.376	1	.123	1.137	.966	1.339

a. The reference category is: 1.00.

The difference model between 1994 and 1999

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.94@99	1.00	84	51.5%
	2.00	54	33.1%
	3.00	25	15.3%
NEIGHBORHOODS IN BLOOM AREA	1	18	11.0%
	2	36	22.1%
	3	109	66.9%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	324.431			
Final	293.671	30.760	18	.031

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	313.095	306	.378
Deviance	293.671	306	.684

Pseudo R-Square

Cox and Snell	.172
Nagelkerke	.199
McFadden	.095

Parameter Estimates

CAT_CH_ HOMICIDE.94@99[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2.00	Intercept	-.774	.235	10.870	1	.001			
	CH_RES_MOBILITY_ 94@99	-.237	.571	.172	1	.678	.789	.257	2.417
	CH_RACE_HTRG_ 94@99	-1.226	3.313	.137	1	.711	.293	.000	193.830
	CH_PR_FDISTRUP_ 94@99	.005	.012	.149	1	.699	1.005	.981	1.029
	CH_SES_94@99	-.330	.460	.515	1	.473	.719	.292	1.770
	CH_P_DENSITY_94@99	.000	.000	.519	1	.471	1.000	.999	1.000
	CH_PR_YOUTH_94@99	.053	.052	1.027	1	.311	1.054	.952	1.167
	CH_PR_VACANT_94@99	.051	.048	1.147	1	.284	1.052	.959	1.155
	[BBLOOM_99=1]	1.402	.675	4.319	1	.038	4.065	1.083	15.257
	[BBLOOM_99=2]	.926	.477	3.763	1	.052	2.523	.990	6.427
	[BBLOOM_99=3]	0[b]	.	.	0	.	.	.	.
3.00	Intercept	-1.627	.334	23.733	1	.000			
	CH_RES_MOBILITY_ 94@99	1.557	.841	3.429	1	.064	4.746	.913	24.670
	CH_RACE_HTRG_ 94@99	1.397	4.672	.089	1	.765	4.044	.000	38331.050
	CH_PR_FDISTRUP_ 94@99	.037	.024	2.392	1	.122	1.038	.990	1.089
	CH_SES_94@99	.318	.715	.198	1	.656	1.375	.339	5.583
	CH_P_DENSITY_94@99	.000	.000	.383	1	.536	1.000	.999	1.001
	CH_PR_YOUTH_94@99	-.095	.063	2.293	1	.130	.909	.804	1.028
	CH_PR_VACANT_94@99	.054	.078	.472	1	.492	1.055	.905	1.231
	[BBLOOM_99=1]	2.046	.775	6.973	1	.008	7.740	1.695	35.352
	[BBLOOM_99=2]	.932	.666	1.956	1	.162	2.540	.688	9.377
	[BBLOOM_99=3]	0[b]	.	.	0	.	.	.	.

a. The reference category is: 1.00.

b. This parameter is set to zero because it is redundant.

The difference model between 1993 and 1994

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.93@94	1.00	84	51.5%
	2.00	29	17.8%
	3.00	50	30.7%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	329.680			
Final	296.810	32.870	14	.003

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	320.318	310	.331
Deviance	296.810	310	.695

Pseudo R-Square

Cox and Snell	.183
Nagelkerke	.210
McFadden	.100

Parameter Estimates

CAT_CH_ HOMICIDE.93@94[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
2.00	Intercept	-1.310	.275	22.640	1	.000			
	CH_RES_MOBILITY_ 93@94	-.282	3.970	.005	1	.943	.754	.000	1808.187
	CH_RACE_HTRG_ 93@94	6.602	21.497	.094	1	.759	736.922	3.71E-016	1.465E+021
	CH_PR_FDISTRUP_ 93@94	-.121	.089	1.845	1	.174	.886	.743	1.055
	CH_SES_93@94	-4.660	3.406	1.871	1	.171	.009	1.19E-005	7.511
	CH_P_DENSITY_93@94	-.004	.002	2.563	1	.109	.996	.992	1.001
	CH_PR_YOUTH_93@94	.689	.340	4.108	1	.043	1.992	1.023	3.878
	CH_PR_VACANT_93@94	.158	.380	.173	1	.678	1.171	.556	2.469
3.00	Intercept	-.834	.233	12.818	1	.000			
	CH_RES_MOBILITY_ 93@94	-5.566	3.474	2.567	1	.109	.004	4.23E-006	3.464
	CH_RACE_HTRG_ 93@94	3.488	18.707	.035	1	.852	32.710	3.90E-015	2.742E+017
	CH_PR_FDISTRUP_ 93@94	-.110	.082	1.799	1	.180	.896	.764	1.052
	CH_SES_93@94	-2.392	2.764	.749	1	.387	.091	.000	20.593
	CH_P_DENSITY_93@94	-.006	.002	7.254	1	.007	.994	.990	.998
	CH_PR_YOUTH_93@94	.399	.279	2.041	1	.153	1.491	.862	2.578
	CH_PR_VACANT_93@94	.647	.341	3.607	1	.058	1.910	.979	3.726

a. The reference category is: 1.00.

The difference model between 1994 and 1995

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.94@95	1.00	82	50.3%
	2.00	51	31.3%
	3.00	30	18.4%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	332.743			
Final	310.350	22.392	14	.071

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	316.949	310	.381
Deviance	310.350	310	.484

Pseudo R-Square

Cox and Snell	.128
Nagelkerke	.148
McFadden	.067

Parameter Estimates

CAT_CH_ HOMICIDE.94@95[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	95% Confidence Interval for Exp(B) Upper Bound
2.00	Intercept	-.545	.217	6.334	1	.012			
	CH_RES_MOBILITY_ 94@95	-5.112	3.179	2.586	1	.108	.006	1.19E-005	3.061
	CH_RACE_HTRG_ 94@95	-12.049	17.920	.452	1	.501	5.85E-006	3.26E-021	1.050E+010
	CH_PR_FDISTRUP_ 94@95	-.089	.074	1.469	1	.226	.915	.792	1.057
	CH_SES_94@95	.172	2.695	.004	1	.949	1.188	.006	233.894
	CH_P_DENSITY_94@95	-.001	.001	.215	1	.643	.999	.997	1.002
	CH_PR_YOUTH_94@95	.383	.259	2.195	1	.138	1.467	.884	2.436
	CH_PR_VACANT_94@95	.465	.311	2.229	1	.135	1.591	.865	2.928
3.00	Intercept	-1.061	.255	17.355	1	.000			
	CH_RES_MOBILITY_ 94@95	-3.588	3.973	.816	1	.366	.028	1.15E-005	66.578
	CH_RACE_HTRG_ 94@95	-30.690	21.259	2.084	1	.149	4.69E-014	3.76E-032	58465.817
	CH_PR_FDISTRUP_ 94@95	-.105	.084	1.559	1	.212	.901	.764	1.061
	CH_SES_94@95	2.436	3.167	.592	1	.442	11.429	.023	5668.326
	CH_P_DENSITY_94@95	.003	.002	1.943	1	.163	1.003	.999	1.006
	CH_PR_YOUTH_94@95	.110	.287	.148	1	.701	1.117	.636	1.960
	CH_PR_VACANT_94@95	1.014	.402	6.349	1	.012	2.755	1.253	6.061

a. The reference category is: 1.00.

The difference model between 1996 and 1997

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.96@97	1.00	91	55.8%
	2.00	29	17.8%
	3.00	43	26.4%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	320.820			
Final	307.545	13.275	14	.505

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	322.643	310	.299
Deviance	307.545	310	.529

Pseudo R-Square

Cox and Snell	.078
Nagelkerke	.091
McFadden	.041

Parameter Estimates

CAT_CH_ HOMICIDE.96@97[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
2.00	Intercept	-1.405	.264	28.279	1	.000			
	CH_RES_MOBILITY_ 96@97	2.557	3.336	.588	1	.443	12.893	.019	8902.997
	CH_RACE_HTRG_ 96@97	25.586	20.634	1.538	1	.215	1E+011	3.53E-007	4.739E+028
	CH_PR_FDISTRUP_ 96@97	-.051	.078	.418	1	.518	.951	.815	1.108
	CH_SES_96@97	2.707	3.009	.810	1	.368	14.991	.041	5459.850
	CH_P_DENSITY_96@97	-.003	.001	4.880	1	.027	.997	.994	1.000
	CH_PR_YOUTH_96@97	.275	.316	.758	1	.384	1.317	.709	2.447
	CH_PR_VACANT_96@97	-.240	.331	.528	1	.467	.786	.411	1.504
3.00	Intercept	-.955	.219	18.986	1	.000			
	CH_RES_MOBILITY_ 96@97	1.764	2.924	.364	1	.546	5.834	.019	1799.500
	CH_RACE_HTRG_ 96@97	16.935	17.235	.965	1	.326	2E+007	4.83E-008	1.060E+022
	CH_PR_FDISTRUP_ 96@97	-.093	.064	2.125	1	.145	.911	.804	1.033
	CH_SES_96@97	2.761	2.602	1.126	1	.289	15.816	.096	2594.700
	CH_P_DENSITY_96@97	-.002	.001	1.392	1	.238	.998	.996	1.001
	CH_PR_YOUTH_96@97	.277	.272	1.038	1	.308	1.319	.774	2.249
	CH_PR_VACANT_96@97	.026	.294	.008	1	.930	1.026	.577	1.826

a. The reference category is: 1.00.

The difference model between 1997 and 1998

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.97@98	1.00	81	49.7%
	2.00	47	28.8%
	3.00	35	21.5%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	337.874			
Final	320.861	17.013	14	.256

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	335.399	310	.154
Deviance	320.861	310	.324

Pseudo R-Square

Cox and Snell	.099
Nagelkerke	.113
McFadden	.050

Parameter Estimates

CAT_CH_HOMICIDE.97@98[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
2.00	Intercept	-.764	.216	12.453	1	.000			
	CH_RES_MOBILITY_97@98	1.329	2.722	.238	1	.625	3.777	.018	784.033
	CH_RACE_HTRG_97@98	-3.696	16.345	.051	1	.821	.025	3.03E-016	2.030E+012
	CH_PR_FDISTRUP_97@98	-.126	.064	3.847	1	.050	.881	.777	1.000
	CH_SES_97@98	-.618	2.337	.070	1	.791	.539	.006	52.539
	CH_P_DENSITY_97@98	.000	.001	.003	1	.959	1.000	.997	1.003
	CH_PR_YOUTH_97@98	.095	.242	.153	1	.695	1.099	.684	1.767
	CH_PR_VACANT_97@98	-.334	.275	1.477	1	.224	.716	.418	1.227
3.00	Intercept	-1.118	.250	20.060	1	.000			
	CH_RES_MOBILITY_97@98	7.954	3.291	5.840	1	.016	2845.620	4.495	1801476.245
	CH_RACE_HTRG_97@98	.648	17.847	.001	1	.971	1.912	1.23E-015	2.971E+015
	CH_PR_FDISTRUP_97@98	-.077	.071	1.162	1	.281	.926	.805	1.065
	CH_SES_97@98	-2.654	2.599	1.042	1	.307	.070	.000	11.483
	CH_P_DENSITY_97@98	-.002	.001	3.034	1	.082	.998	.995	1.000
	CH_PR_YOUTH_97@98	-.060	.303	.039	1	.844	.942	.520	1.706
	CH_PR_VACANT_97@98	-.209	.298	.490	1	.484	.812	.453	1.456

a. The reference category is: 1.00.

The difference model between 1998 and 1999

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.98@99	1.00	94	57.7%
	2.00	41	25.2%
	3.00	28	17.2%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	315.307			
Final	301.349	13.958	14	.453

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	316.658	310	.385
Deviance	301.349	310	.627

Pseudo R-Square

Cox and Snell	.082
Nagelkerke	.096
McFadden	.044

Parameter Estimates

CAT_CH_ HOMICIDE.98@99[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
2.00	Intercept	-.972	.225	18.614	1	.000			
	CH_RES_MOBILITY_ 98@99	2.490	2.495	.996	1	.318	12.065	.091	1605.811
	CH_RACE_HTRG_ 98@99	-1.874	15.316	.015	1	.903	.153	1.41E-014	1.671E+012
	CH_PR_FDISTRUP_ 98@99	-.053	.054	.962	1	.327	.949	.854	1.054
	CH_SES_98@99	-.324	1.898	.029	1	.864	.723	.018	29.815
	CH_P_DENSITY_98@99	-.002	.001	2.108	1	.146	.998	.996	1.001
	CH_PR_YOUTH_98@99	.144	.276	.271	1	.602	1.155	.672	1.983
	CH_PR_VACANT_98@99	.180	.182	.970	1	.325	1.197	.837	1.710
3.00	Intercept	-1.332	.263	25.614	1	.000			
	CH_RES_MOBILITY_ 98@99	6.290	3.026	4.321	1	.038	539.330	1.433	203049.404
	CH_RACE_HTRG_ 98@99	3.343	17.910	.035	1	.852	28.307	1.61E-014	4.977E+016
	CH_PR_FDISTRUP_ 98@99	-.032	.073	.195	1	.659	.968	.839	1.117
	CH_SES_98@99	1.003	2.532	.157	1	.692	2.726	.019	390.155
	CH_P_DENSITY_98@99	.000	.002	.052	1	.820	1.000	.996	1.003
	CH_PR_YOUTH_98@99	-.306	.274	1.251	1	.263	.736	.430	1.259
	CH_PR_VACANT_98@99	.071	.201	.126	1	.723	1.074	.724	1.593

a. The reference category is: 1.00.

The difference model between 1997 and 1999

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.97@99	1.00	95	58.3%
	2.00	47	28.8%
	3.00	21	12.9%
NEIGHBORHOODS IN BLOOM AREA	1	18	11.0%
	2	36	22.1%
	3	109	66.9%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	305.542			
Final	271.398	34.145	18	.012

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	320.496	306	.273
Deviance	271.398	306	.923

Pseudo R-Square

Cox and Snell	.189
Nagelkerke	.223
McFadden	.112

Parameter Estimates

CAT_CH_ HOMICIDE.97@99[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2.00	Intercept	-1.362	.266	26.163	1	.000			
	CH_RES_MOBILITY_ 97@99	-.972	1.263	.593	1	.441	.378	.032	4.493
	CH_RACE_HTRG_ 97@99	-6.078	8.242	.544	1	.461	.002	2.21E-010	23781.458
	CH_PR_FDISTRUP_ 97@99	-.086	.032	7.015	1	.008	.918	.861	.978
	CH_SES_97@99	2.175	1.025	4.505	1	.034	8.799	1.181	65.544
	CH_P_DENSITY_97@99	.000	.001	.137	1	.712	1.000	.999	1.002
	CH_PR_YOUTH_97@99	.050	.126	.157	1	.692	1.051	.821	1.347
	CH_PR_VACANT_97@99	-.064	.086	.558	1	.455	.938	.792	1.110
	[BBLOOM_99=1]	2.424	.745	10.576	1	.001	11.289	2.620	48.651
	[BBLOOM_99=2]	.360	.510	.497	1	.481	1.433	.527	3.896
	[BBLOOM_99=3]	0[b]	.	.	0	.	.	.	.
3.00	Intercept	-2.132	.369	33.412	1	.000			
	CH_RES_MOBILITY_ 97@99	2.326	1.807	1.657	1	.198	10.239	.296	353.612
	CH_RACE_HTRG_ 97@99	-2.823	10.979	.066	1	.797	.059	2.69E-011	131491583.7
	CH_PR_FDISTRUP_ 97@99	-.023	.049	.234	1	.629	.977	.888	1.074
	CH_SES_97@99	2.169	1.568	1.915	1	.166	8.753	.405	189.009
	CH_P_DENSITY_97@99	.000	.001	.002	1	.961	1.000	.998	1.002
	CH_PR_YOUTH_97@99	-.177	.156	1.292	1	.256	.837	.617	1.137
	CH_PR_VACANT_97@99	-.040	.150	.071	1	.790	.961	.716	1.289
	[BBLOOM_99=1]	2.452	.849	8.335	1	.004	11.610	2.198	61.338
	[BBLOOM_99=2]	.761	.656	1.346	1	.246	2.141	.592	7.745
	[BBLOOM_99=3]	0[b]	.	.	0	.	.	.	.

a. The reference category is: 1.00.

b. This parameter is set to zero because it is redundant.

The difference model between 1997 and 1998 (NEW)

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.97@98	1.00	81	49.7%
	2.00	47	28.8%
	3.00	35	21.5%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	337.874			
Final	327.350	10.524	12	.570

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	328.357	312	.251
Deviance	327.350	312	.264

Pseudo R-Square

Cox and Snell	.063
Nagelkerke	.072
McFadden	.031

Parameter Estimates

CAT_CH_ HOMICIDE.97@98[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2.00	Intercept	-.763	.216	12.435	1	.000			
	CH_RACE_HTRG_ 97@98	-4.589	16.226	.080	1	.777	.010	1.57E-016	6.590E+011
	CH_PR_FDISTRUP_ 97@98	-.121	.063	3.612	1	.057	.886	.783	1.004
	CH_SES_97@98	-.418	2.298	.033	1	.856	.658	.007	59.459
	CH_P_DENSITY_97@98	.000	.001	.009	1	.924	1.000	.997	1.003
	CH_PR_YOUTH_97@98	.125	.234	.287	1	.592	1.134	.717	1.793
	CH_PR_VACANT_97@98	-.306	.270	1.290	1	.256	.736	.434	1.249
3.00	Intercept	-1.004	.234	18.380	1	.000			
	CH_RACE_HTRG_ 97@98	.977	17.767	.003	1	.956	2.656	2.00E-015	3.532E+015
	CH_PR_FDISTRUP_ 97@98	-.061	.069	.780	1	.377	.941	.821	1.078
	CH_SES_97@98	-1.233	2.471	.249	1	.618	.292	.002	36.986
	CH_P_DENSITY_97@98	-.002	.001	2.485	1	.115	.998	.995	1.001
	CH_PR_YOUTH_97@98	.149	.259	.332	1	.564	1.161	.699	1.928
	CH_PR_VACANT_97@98	-.078	.290	.072	1	.789	.925	.524	1.633

a. The reference category is: 1.00.

The difference model between 1998 and 1999 (NEW)

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.98@99	1.00	94	57.7%
	2.00	41	25.2%
	3.00	28	17.2%
NEIGHBORHOODS IN BLOOM AREA	1	18	11.0%
	2	36	22.1%
	3	109	66.9%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	315.307			
Final	288.428	26.879	16	.043

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	320.724	308	.297
Deviance	288.428	308	.782

Pseudo R-Square

Cox and Snell	.152
Nagelkerke	.178
McFadden	.085

Parameter Estimates

CAT_CH_HOMICIDE.98@99[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2.00	Intercept	-1.200	.267	20.167	1	.000			
	CH_RACE_HTRG_98@99	-5.066	16.132	.099	1	.753	.006	1.17E-016	3.399E+011
	CH_PR_FDISTRUP_98@99	-.040	.057	.500	1	.479	.961	.859	1.074
	CH_SES_98@99	.108	1.932	.003	1	.955	1.115	.025	49.143
	CH_P_DENSITY_98@99	-.002	.001	1.694	1	.193	.998	.996	1.001
	CH_PR_YOUTH_98@99	.255	.272	.880	1	.348	1.290	.758	2.198
	CH_PR_VACANT_98@99	.133	.177	.562	1	.454	1.142	.807	1.617
	[BBLOOM_99=1]	2.485	.835	8.851	1	.003	12.001	2.335	61.687
	[BBLOOM_99=2]	.080	.516	.024	1	.877	1.083	.394	2.978
	[BBLOOM_99=3]	0[b]	.	.	0	.	.	.	.
3.00	Intercept	-1.489	.300	24.675	1	.000			
	CH_RACE_HTRG_98@99	-.328	19.114	.000	1	.986	.720	3.87E-017	1.342E+016
	CH_PR_FDISTRUP_98@99	-.006	.078	.006	1	.938	.994	.853	1.159
	CH_SES_98@99	2.357	2.694	.766	1	.381	10.564	.054	2073.169
	CH_P_DENSITY_98@99	-.001	.002	.175	1	.676	.999	.996	1.002
	CH_PR_YOUTH_98@99	-.055	.260	.045	1	.833	.947	.569	1.575
	CH_PR_VACANT_98@99	.045	.265	.029	1	.864	1.046	.623	1.757
	[BBLOOM_99=1]	2.676	.866	9.540	1	.002	14.530	2.659	79.396
	[BBLOOM_99=2]	-.227	.647	.123	1	.726	.797	.224	2.833
	[BBLOOM_99=3]	0[b]	.	.	0	.	.	.	.

a. The reference category is: 1.00.

b. This parameter is set to zero because it is redundant.

The difference model between 1993 and 1994 (NEW)

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.93@94	1.00	84	51.5%
	2.00	29	17.8%
	3.00	50	30.7%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	329.680			
Final	296.911	32.768	12	.001

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	320.256	312	.362
Deviance	296.911	312	.721

Pseudo R-Square

Cox and Snell	.182
Nagelkerke	.210
McFadden	.099

Parameter Estimates

CAT_CH_ HOMICIDE.93@94[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2.00	Intercept	-1.286	.263	23.920	1	.000			
	CH_RES_MOBILITY_ 93@94	-.377	3.969	.009	1	.924	.686	.000	1639.975
	CH_PR_FDISTRUP_ 93@94	-.116	.088	1.752	1	.186	.890	.750	1.057
	CH_SES_93@94	-4.745	3.399	1.948	1	.163	.009	1.11E-005	6.804
	CH_P_DENSITY_93@94	-.003	.002	2.530	1	.112	.997	.992	1.001
	CH_PR_YOUTH_93@94	.700	.337	4.311	1	.038	2.014	1.040	3.901
	CH_PR_VACANT_93@94	.144	.378	.145	1	.704	1.155	.550	2.424
3.00	Intercept	-.820	.222	13.703	1	.000			
	CH_RES_MOBILITY_ 93@94	-5.632	3.462	2.647	1	.104	.004	4.05E-006	3.168
	CH_PR_FDISTRUP_ 93@94	-.106	.080	1.751	1	.186	.900	.769	1.052
	CH_SES_93@94	-2.393	2.760	.752	1	.386	.091	.000	20.407
	CH_P_DENSITY_93@94	-.006	.002	7.221	1	.007	.994	.990	.998
	CH_PR_YOUTH_93@94	.402	.278	2.095	1	.148	1.496	.867	2.579
	CH_PR_VACANT_93@94	.637	.338	3.545	1	.060	1.890	.974	3.667

a. The reference category is: 1.00.

The difference model between 1996 and 1997 (NEW)

Case Processing Summary

		N	Marginal Percentage
CAT_CH_ HOMICIDE.96@97	1.00	91	55.8%
	2.00	29	17.8%
	3.00	43	26.4%
Valid		163	100.0%
Missing		0	
Total		163	
Subpopulation		163[a]	

a. The dependent variable has only one value observed in 163 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	320.820			
Final	309.571	11.249	12	.508

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	324.726	312	.298
Deviance	309.571	312	.528

Pseudo R-Square

Cox and Snell	.067
Nagelkerke	.078
McFadden	.035

Parameter Estimates

CAT_CH_HOMICIDE.96@97[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2.00	Intercept	-1.346	.256	27.701	1	.000			
	CH_RES_MOBILITY_96@97	2.373	3.361	.498	1	.480	10.724	.015	7779.248
	CH_PR_FDISTRUP_96@97	-.039	.078	.248	1	.618	.962	.826	1.121
	CH_SES_96@97	2.535	3.032	.699	1	.403	12.621	.033	4807.444
	CH_P_DENSITY_96@97	-.003	.001	4.359	1	.037	.997	.994	1.000
	CH_PR_YOUTH_96@97	.293	.317	.856	1	.355	1.340	.721	2.493
	CH_PR_VACANT_96@97	-.289	.330	.765	1	.382	.749	.392	1.431
3.00	Intercept	-.925	.216	18.432	1	.000			
	CH_RES_MOBILITY_96@97	1.598	2.918	.300	1	.584	4.941	.016	1505.019
	CH_PR_FDISTRUP_96@97	-.084	.062	1.839	1	.175	.920	.815	1.038
	CH_SES_96@97	2.567	2.593	.980	1	.322	13.025	.081	2099.462
	CH_P_DENSITY_96@97	-.002	.001	1.323	1	.250	.998	.996	1.001
	CH_PR_YOUTH_96@97	.293	.270	1.174	1	.279	1.340	.789	2.277
	CH_PR_VACANT_96@97	-.004	.292	.000	1	.990	.996	.562	1.767

a. The reference category is: 1.00.

APPENDIX E

STEPWISE MULTIPLE REGRESSION OUTPUTS

Correlations

		AVG_HOM_RATE	AVG_RES_MOBILITY	AVG_RACE_HTRG	AVG_PR_FDISTRUP	AVG_SES	AVG_PDENSITY	AVG_PR_YOUTH	AVG_PR_VACANT
Pearson Correlation	AVG_HOM_RATE	1.000	-.036	-.260	.534	.586	-.398	-.132	.427
	AVG_RES_MOBILITY	-.036	1.000	.281	.166	.126	.538	.423	-.043
	AVG_RACE_HTRG	-.260	.281	1.000	-.193	-.413	.033	.139	-.106
	AVG_PR_FDISTRUP	.534	.166	-.193	1.000	.814	-.213	.087	.059
	AVG_SES	.586	.126	-.413	.814	1.000	-.152	.124	.097
	AVG_PDENSITY	-.398	.538	.033	-.213	-.152	1.000	.291	-.242
	AVG_PR_YOUTH	-.132	.423	.139	.087	.124	.291	1.000	-.204
	AVG_PR_VACANT	.427	-.043	-.106	.059	.097	-.242	-.204	1.000
Sig. (1-tailed)	AVG_HOM_RATE	.	.389	.017	.000	.000	.000	.145	.000
	AVG_RES_MOBILITY	.389	.	.011	.092	.157	.000	.000	.366
	AVG_RACE_HTRG	.017	.011	.	.060	.000	.396	.132	.199
	AVG_PR_FDISTRUP	.000	.092	.060	.	.000	.043	.242	.318
	AVG_SES	.000	.157	.000	.000	.	.112	.160	.219
	AVG_PDENSITY	.000	.000	.396	.043	.112	.	.009	.025
	AVG_PR_YOUTH	.145	.000	.132	.242	.160	.009	.	.050
	AVG_PR_VACANT	.000	.366	.199	.318	.219	.025	.050	.
N	AVG_HOM_RATE	66	66	66	66	66	66	66	66
	AVG_RES_MOBILITY	66	66	66	66	66	66	66	66
	AVG_RACE_HTRG	66	66	66	66	66	66	66	66
	AVG_PR_FDISTRUP	66	66	66	66	66	66	66	66
	AVG_SES	66	66	66	66	66	66	66	66
	AVG_PDENSITY	66	66	66	66	66	66	66	66
	AVG_PR_YOUTH	66	66	66	66	66	66	66	66
	AVG_PR_VACANT	66	66	66	66	66	66	66	66

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.586[a]	.344	.334	.63560
2	.694[b]	.482	.465	.56926
3	.732[c]	.536	.514	.54283

a. Predictors: (Constant), AVG_SES

b. Predictors: (Constant), AVG_SES, AVG_PR_VACANT

c. Predictors: (Constant), AVG_SES, AVG_PR_VACANT, AVG_PDENSITY

d. Dependent Variable: AVG_HOM_RATE

ANOVA[d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.548	1	13.548	33.535	.000[a]
	Residual	25.855	64	.404		
	Total	39.403	65			
2	Regression	18.987	2	9.493	29.295	.000[b]
	Residual	20.416	63	.324		
	Total	39.403	65			
3	Regression	21.133	3	7.044	23.906	.000[c]
	Residual	18.270	62	.295		
	Total	39.403	65			

a. Predictors: (Constant), AVG_SES

b. Predictors: (Constant), AVG_SES, AVG_PR_VACANT

c. Predictors: (Constant), AVG_SES, AVG_PR_VACANT, AVG_PDENSITY

d. Dependent Variable: AVG_HOM_RATE

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.774	.091		8.550	.000					
	AVG_SES	.467	.081	.586	5.791	.000	.586	.586	.586	1.000	1.000
2	(Constant)	.253	.151		1.681	.098					
	AVG_SES	.438	.073	.550	6.037	.000	.586	.605	.548	.991	1.010
	AVG_PR_VACANT	.043	.011	.373	4.097	.000	.427	.459	.372	.991	1.010
3	(Constant)	.667	.210		3.174	.002					
	AVG_SES	.413	.070	.519	5.917	.000	.586	.601	.512	.973	1.028
	AVG_PR_VACANT	.037	.010	.318	3.558	.001	.427	.412	.308	.938	1.066
	AVG_PDENSITY	-4.3E-005	.000	-.243	-2.699	.009	-.398	-.324	-.233	.925	1.081

a. Dependent Variable: AVG_HOM_RATE

Excluded Variables[d]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	AVG_RES_MOBILITY	-.111[a]	-1.091	.280	-.136	.984	1.016	.984
	AVG_RACE_HTRG	-.022[a]	-.196	.845	-.025	.829	1.206	.829
	AVG_PR_FDISTRUP	.167[a]	.960	.341	.120	.338	2.958	.338
	AVG_PDENSITY	-.316[a]	-3.322	.001	-.386	.977	1.024	.977
	AVG_PR_YOUTH	-.208[a]	-2.094	.040	-.255	.985	1.016	.985
	AVG_PR_VACANT	.373[a]	4.097	.000	.459	.991	1.010	.991
2	AVG_RES_MOBILITY	-.091[b]	-.989	.327	-.125	.981	1.019	.974
	AVG_RACE_HTRG	.008[b]	.075	.940	.010	.825	1.212	.825
	AVG_PR_FDISTRUP	.189[b]	1.217	.228	.153	.338	2.961	.336
	AVG_PDENSITY	-.243[b]	-2.699	.009	-.324	.925	1.081	.925
	AVG_PR_YOUTH	-.133[b]	-1.429	.158	-.179	.938	1.067	.938
3	AVG_RES_MOBILITY	.066[c]	.613	.542	.078	.661	1.514	.623
	AVG_RACE_HTRG	-.006[c]	-.057	.954	-.007	.823	1.215	.810
	AVG_PR_FDISTRUP	.125[c]	.827	.411	.105	.328	3.047	.328
	AVG_PR_YOUTH	-.071[c]	-.759	.450	-.097	.864	1.157	.853

a. Predictors in the Model: (Constant), AVG_SES

b. Predictors in the Model: (Constant), AVG_SES, AVG_PR_VACANT

c. Predictors in the Model: (Constant), AVG_SES, AVG_PR_VACANT, AVG_PDENSITY

d. Dependent Variable: AVG_HOM_RATE

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	AVG_SES	AVG_PR_VACANT	AVG_PDENSITY
1	1	1.504	1.000	.25	.25		
	2	.496	1.741	.75	.75		
2	1	2.266	1.000	.04	.08	.04	
	2	.615	1.919	.04	.92	.05	
	3	.119	4.371	.93	.00	.92	
3	1	2.949	1.000	.01	.03	.02	.02
	2	.700	2.053	.00	.86	.00	.04
	3	.284	3.220	.00	.08	.38	.38
	4	.067	6.642	.98	.03	.60	.56

a. Dependent Variable: AVG_HOM_RATE

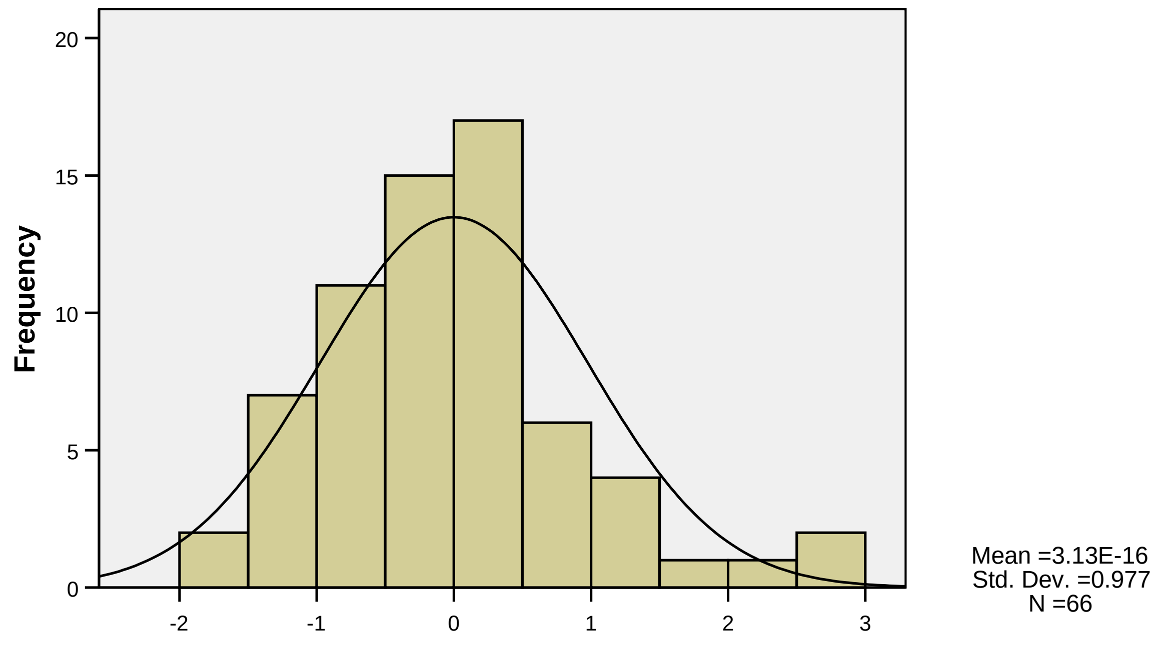
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-.0658	2.6410	1.0387	.57020	66
Residual	-.92439	1.62450	.00000	.53016	66
Std. Predicted Value	-1.937	2.810	.000	1.000	66
Std. Residual	-1.703	2.993	.000	.977	66

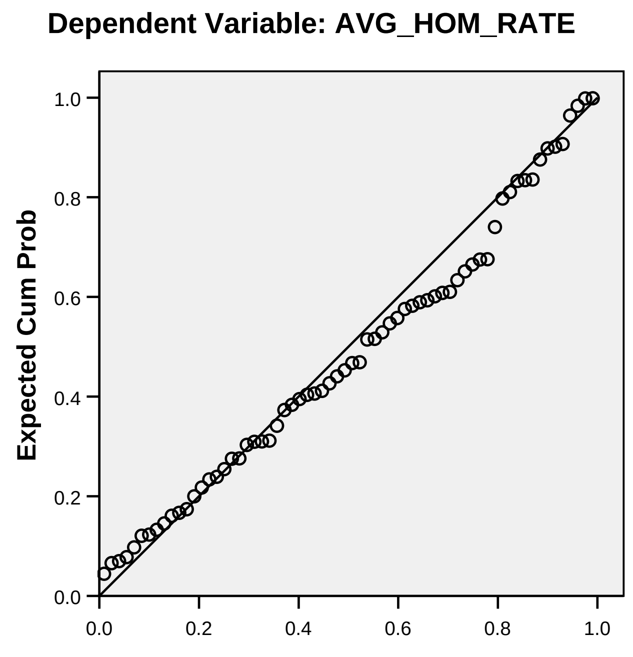
a. Dependent Variable: AVG_HOM_RATE

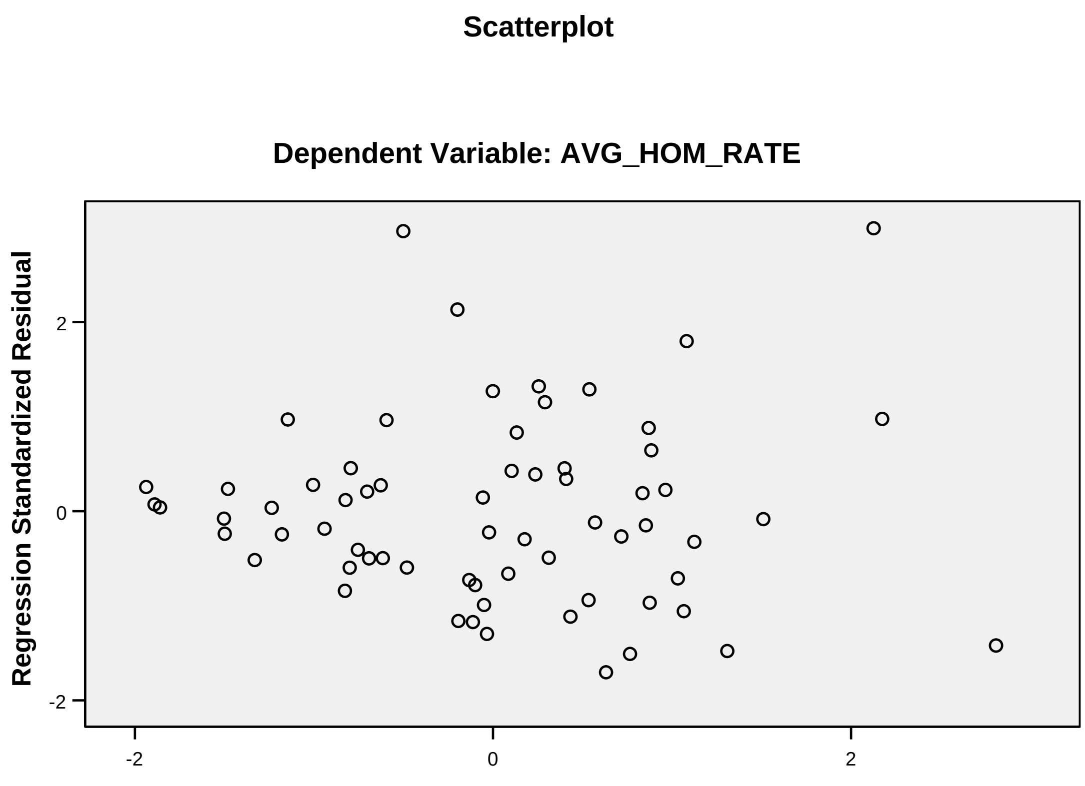
Histogram

Dependent Variable: AVG_HOM_RATE

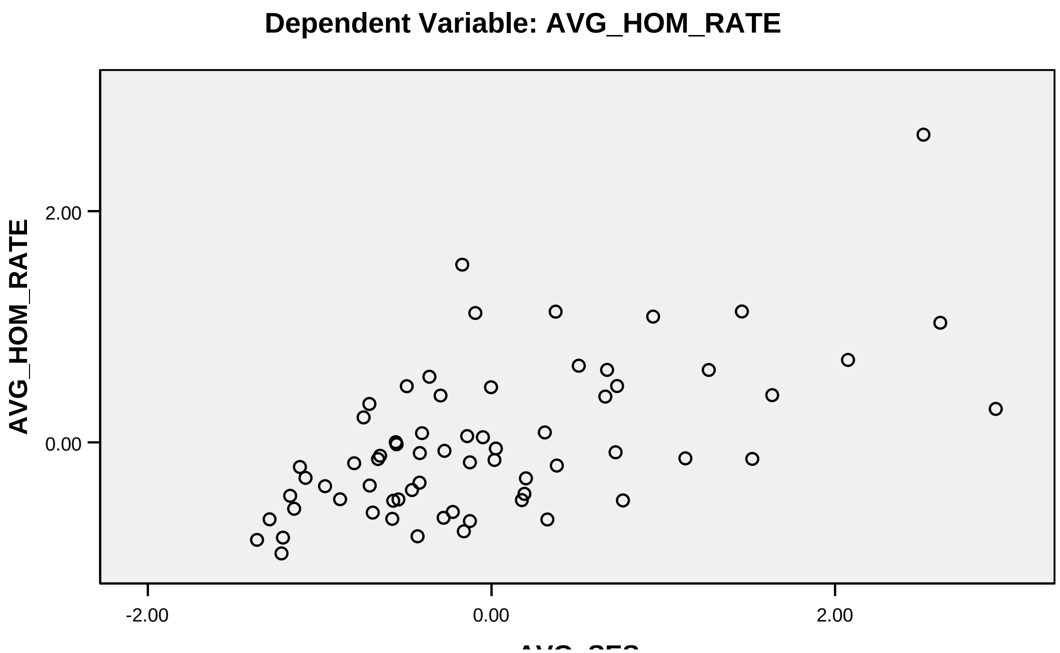


Normal P-P Plot of Regression Standardized Residual



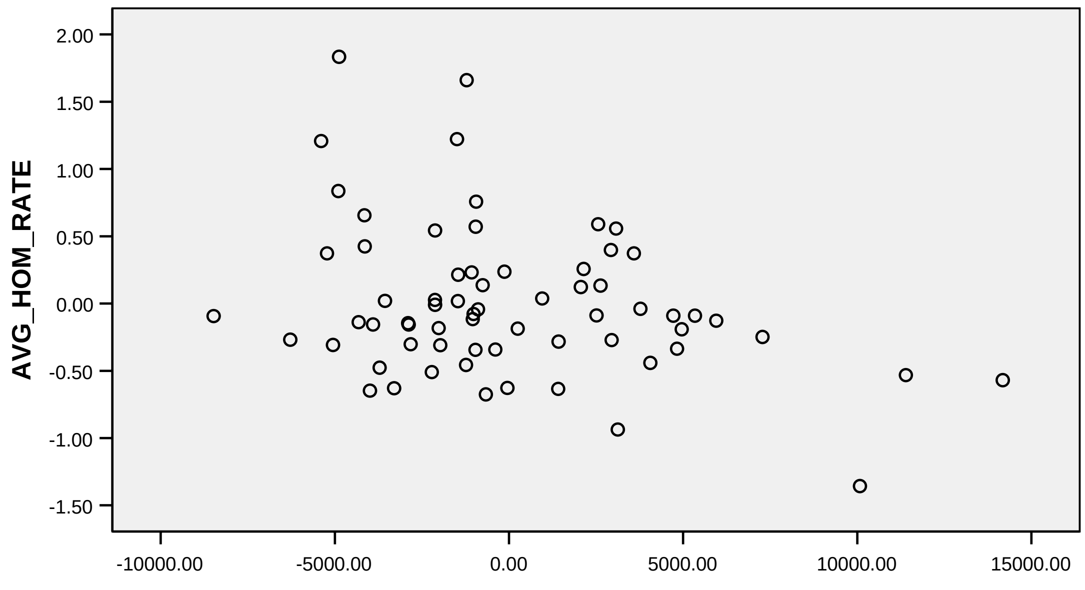

Scatterplot
Dependent Variable: AVG_HOM_RATE
Regression Standardized Residual
2
0
-2
-2
0
2

Partial Regression Plot



Partial Regression Plot

Dependent Variable: AVG_HOM_RATE



Vita

Suleyman Demirci was born on February 9, 1970 in Istanbul/Turkey. He graduated from Middle East Technical University. His bachelor degree is from Physics. He earned his Master of Science degree from Criminal Justice at University of North Texas, Denton. He has been working for twelve years in Turkish National Police. He has recently been studying Geographic Information Systems (GIS), Intelligence Led-Policing, spatial/advanced multivariate statistics, collective efficacy, quality of life, and spatially integrated public policy analysis. He is currently married and has two kids.