DIFFUSION OF POLICE TECHNOLOGY ACROSS TIME AND SPACE AND THE IMPACT OF TECHNOLOGY USE ON POLICE EFFECTIVENESS AND ITS CONTRIBUTION TO DECISION-MAKING

A dissertation submitted to Kent State University in partial fulfillment of the requirements for the degree of Doctor of Philosophy

by

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This was an amazing and a fantastic quest, not quite like the quests in the fantasy literature, but a fantastic quest nonetheless. I had a task to complete, I had a fellowship and mentors and enemies and even a nemesis. Well, my nemesis was not a person or a thing or not even a dragon; it was no other than an inner turmoil in the name of procrastination. But I have defeated it and emerged victorious from this quest, but I certainly was not alone in this perilous adventure.

The companions in the fellowship were the dearest to my heart, my caring family members, my never-criticizing-ever-encouraging-friends and, my wife, my love, Zerrin Nur Demir, who sacrificed the most.

My mentors were like master magicians teaching their art with perseverance. Ryan Claassen was like a potion master, dedicated, patient, careful and smart. Jay Lee was like a wand master, swift, ambidextrous and quick-witted. Renee Johnson was like a good witch, a prolific sorceress, who pops out of thin air when you need her the most. Mark Colvin was the Archmage; learned, full of experience, prompt and always to-the-point.

My parents had to suffer years of separation during this quest and now that I have become a father myself I can understand better what they must have gone through. They deserve praise in patience. Also my brother had suffered a lot. He had to go hunting,
spear fishing, swimming and scavenging ripened fruits in our farm without me and that was a great sacrifice.

I want to thank my martial arts comrades for their long distance chi energy support, Serkan the Long Hair, Namik the Brain Surgeon (literally), Atik the Devourer with whom I have been practicing Avci Wing Tsun and Escrima, a mixed martial arts style that has been a second life for me for the last decade or more. Special thanks go to my Grand Master Sifu Salih Avci, who encouraged me by saying that there is always time to learn martial arts but doctorate is once in a life time opportunity and my Master Sihing Hasan Akin, who had always found something to do for me with regards to martial arts even from thousands of miles away to keep some of my hidden martial arts coals still burning among academic ashes of physical laziness and sedentary.
CHAPTER 1

INTRODUCTION

Overview of the Study and Summary of the Findings

Use of information technologies and special technologies such as crime analysis and crime mapping are practical ways to predict and solve crimes and thus increase the effectiveness and efficiency of a police organization.

By providing law enforcement officials with resources for more proactive policing, crime mapping enables police managers to allocate their resources more effectively and distribute their forces more efficiently. Crime analysis and especially crime mapping, when effectively conducted and evaluated, can be assets to the police department in their various activities and to the police manager in decision-making.

Current use, however, of crime analysis and crime mapping in police departments across the United States (U.S.) is not yet strategic. Police can produce volumes and computer loads of intelligence and information, which only becomes useful operationally after being interpreted, evaluated, assessed and any potential patterns and linkages investigated.
While the direct effect of crime analysis and crime mapping on fighting crime is not clearly established by empirical studies, the literature suggests that these technologies are widely used in local police departments across the U.S. (Mamalian & La Vigne, 1999; O'Shea & Nicholls, 2003; Weisburd & Lum, 2005; Weisburd & McEwen, 1998). The widespread and swift adoption of those technologies across the police departments, especially after the 1990s, is also inadequately studied. Available studies at the national level are narrow in terms of the data used and are merely descriptive. Moreover, those that provide empirical evidence are mainly limited to state level.

A better understanding of the diffusion of advanced analytical tools, especially crime mapping, across police departments in time and space will first of all enhance our overall knowledge of the diffusion of technological innovation and also enable us to predict patterns of how police technologies spread. More broadly, an understanding of how new technological innovations find their way into the problem solving activities of police departments will help us develop, particularly for public sector organizations, a theoretical understanding of the processes of innovation and diffusion and also provide us with an understanding of promoting productivity change at the local level.

The argument in this study, about the spread of crime mapping, is that crime mapping, as a technological innovation, has diffused among police departments following the pattern proposed in the diffusion of innovations literature and that there is a spatial aspect to this diffusion. In other words, crime mapping technology is more likely to be adopted by police departments that have neighboring police departments that had adopted crime mapping before them.
In fact, the results of the analyses conducted in this study show that there is a spatial aspect to the diffusion of crime mapping technology across police departments in the U.S. Geographically closer departments are more likely to adopt crime mapping technologies.

In what manner the adopting departments use crime mapping is another mystery in the literature. One of the most important aspects of using technology in policing is acquisition and use of information. Recently, two new themes have emerged in policing; evidence-based policing and intelligence led policing. Evidence-based policing for crime prevention emphasizes decision-making based on scientific evidence in the form of empirical research and analysis of data on crime (Welsh, 2006). Intelligence led policing, on the other hand, focuses on identification and quantification of key criminal activities based on analysis and evaluation of various data (Ratcliffe, 2008).

The idea behind those two approaches is to help police executives and managers make informed decisions in dealing with crises and change occurring in their respective environments and their organizations. The key decisions made by these leaders are distinct from those on the spot decisions often made by street-level or mid-level officers in in-field situations. In most instances, there is adequate time for police managers to reflect, assess, and collect additional data in order to make more informed decisions (Morreale, Bond, & Dahlin, 2003; Nutt, 1984).

There is limited research available on police manager’s decision-making, including the area of informed decision-making in policing. However, this topic is quite important to benefit future and current police administrators. Most criminal justice
researchers have focused on decision-making of the line level personnel and have paid scant attention to decision-making of the police manager and the various elements of effective decision-making processes. This important aspect of policing is equally, if not more, important to the future of the policing industry than street level decision-making of the patrol officers or detectives (Morreale, et al., 2003).

In that sense, this study also examines whether the information obtained from crime mapping has an impact on managerial decision-making in police departments. The theoretical argument behind the analysis is that while some claim that more information is good in decision-making since it increases the ability of the decision maker to make rational decisions, others maintain that too much information is hard to assess and evaluate for the purposes of decision-making due to time restrictions and analytical capabilities of the decision maker. In essence, the empirical analyses I conduct in this dissertation yield results supporting the latter argument. To a certain extent police departments are likely to use information obtained from crime mapping in resource allocation and redistricting decisions, however, when the amount of information increases too much the departments are less likely to base such critical decisions on information acquired from crime mapping.

Vann & Garson, 2003; Walter, 2003; Woodby, 2003), the impact of those technologies on crime prevention and crime reduction at the national level is yet to be tested. There are only limited studies on the use of crime analysis and crime mapping by the police and only a few have attempted to measure the impact of those technologies on police effectiveness (Eck & Maguire, 2000; Garicano & Heaton, 2006; Manning, 2001; Meehan, 1998; Weisburd & McEwen, 1998). Thus, there is a gap in the literature about the impact of technology use on police overall effectiveness in terms of increasing clearances. Specifically, the literature lacks generalizable empirical evidence showing that crime analysis and crime mapping, two fast spreading technologies, increase police’s crime solving capabilities, enhance enforcement and improve crime prevention on a broader scale.

If the effectiveness of crime analysis and crime mapping adoption as powerful analytic tools in crime prevention and crime reduction can be presented, further studies to find better ways to get the most out of crime analysis and crime mapping can be done. Moreover, police departments that have already invested or that are planning to invest large amounts of capital and resources in those technologies can know whether their expenditure is or would be cost effective. If such is the case, police departments that have adopted crime analysis and crime mapping can invest more and explore novel ways of making those tools more efficient. Also departments that are reluctant to adopt those technologies can have a better idea of whether to invest money in and allocate human resources for crime analysis and crime mapping.

The theoretical argument here is that by enabling the police to be present at the
right place at the right time by taking advantage of analysis of previous crime, crime analysis and crime mapping help increase crime clearances. In fact, based on two different methodologies I employ in this research, I find partial evidence that crime mapping and crime analysis help police increase crime clearances controlling for other department level factors and jurisdictional characteristics.

Dissertation Outline

This study argues that use of crime analysis and crime mapping can prevent and help police solve crimes when necessary resources are allocated to those technologies. Also it is posited in this study that crime mapping aids police managers in the decision-making process by providing them with essential and pertinent information about where and how to allocate their resources and shape jurisdictional territories. While diffusion of crime mapping and its effect on decision-making are the main subject matter in the first two empirical chapters, use of crime analysis by the police is added along with crime mapping in the discussion and incorporated in the statistical analyses in the third empirical chapter.

Based on the gap in the literature, I focus on three different but complementary aspects of crime analysis and crime mapping use by police departments: (1) diffusion of crime mapping, (2) contribution of information obtained from crime mapping in decision-making, and (3) impact of crime analysis and crime mapping use on police effectiveness. The connection between those themes is that each theme builds upon the other via the following logic by asking those set of questions: Do police departments have crime
mapping? If they have it, are they using it? And, if they are using it, is it effective? Thus, this study has three distinct yet intertwined empirical chapters that center on each of those themes.

Following the introductory chapter, I discuss the research objectives, present the research questions and explain the data and measures used in the subsequent chapters in Chapter 2. Specifically, I describe the data sets used in this dissertation, their limitations and strengths, and the process of merging the police department and aggregate level data sets.

In Chapter 3, I study the diffusion of crime mapping technology among police departments in the U.S. The main objective in this chapter is to explain police use of crime mapping from a diffusion of innovations perspective. This involves the discussion of the emergence, prevalent use and swift adoption of crime mapping in policing.

In Chapter 4, I study the effect of information obtained from crime mapping on decision-making of the police manager. The goal here is to create an information based decision-making model that explains the contribution of information obtained from crime analysis and crime mapping in decision-making.

In Chapter 5, I examine the effect of crime mapping and crime analysis on crime clearances. The purpose of this chapter is to measure the impact of crime mapping and crime analysis on police effectiveness in terms of increasing crime clearances controlling for department level characteristics and other environmental and demographic factors derived from main criminological theories. In that sense, the analyses in Chapter 3 not only tests the effectiveness of crime fighting technologies but also other aggregate
dynamics that have been shown in the literature to affect crime and correlates of crime.

In each of the empirical chapters, I first establish the conceptual and theoretical frameworks that I briefly explained in this introduction. After outlining and explaining the subject matter of the research, and providing the theoretical background, I present the hypotheses, methodology, analyses and the results.

In the last chapter of the dissertation, I revisit and reevaluate the results of the analyses in the empirical chapters in light of possible policy implications. Moreover, I discuss limitations and contributions of this study and present future research suggestions.
Introduction

The empirical analyses employed in this study are based on a unique data set created by merging several well known data collections. The main goal of this chapter is to describe those data collections in conjunction with the general research objectives and research questions. Specifically, I tie the research objectives and research questions to the data sets and measures used in the research. Thus, this chapter also aims to briefly explain the measures used in the subsequent chapters of this study with a specific focus on the data set from which each measure comes.

Research Objectives

There are three main objectives of this dissertation. The dissertation begins by seeking explanations for swift adoption of crime mapping technology among county and city police departments in the U.S. and the goal here is to determine whether the crime mapping innovation diffused within a spatial pattern. The second goal is to discuss and investigate the usefulness of those technologies in informing the decision-making processes in police organizations, especially in terms of managerial decision-making. The
final goal is to study the question of whether crime analysis and crime mapping use has any effect on crime clearances as a measure of police output.

**Research Questions**

This study addresses a variety of questions related to the causes and consequences of policy innovation by studying in detail the case of crime mapping. The following research questions have emerged after the investigation of the literature and are based on the logical gaps in the literature.

1. Does geographical proximity matter in adoption of crime mapping technology by police departments in the U.S?
2. Is the information obtained from crime mapping used in administrative decision-making in police departments?
3. Does technology use (crime analysis and crime mapping) increase police effectiveness in terms of increasing crime clearances?

**Measures and Data Sources**

In order to measure the impact of crime analysis and crime mapping on police effectiveness, a data set that includes variables measuring crime analysis and crime mapping use, and police effectiveness is necessary for the empirical analyses in Chapter 5. This data set should also include variables derived from criminological theories in order to control for spuriousness and single out the effect of crime analysis and crime mapping use on crime clearances.
Police effectiveness can be operationalized using several criteria such as arrest rates, crime rates, clearances, citations, use of force incidents and civilian complaints (Skogan & Frydl, 2004), however, in this research I measure police effectiveness by using number of crime clearances by arrest per population following other examples in the literature (Garicano & Heaton, 2006; Loveday, 2000; Votey & Phillips, 1972). Uniform Crime Reports (UCR) provides crime clearance rates at police department level in the U.S.

Crime analysis and crime mapping use are measured using the variables in the Law Enforcement Management and Administration Survey (LEMAS) and the Use of Computerized Crime Mapping by Law Enforcement in the U.S. (CCMLE) data sets. LEMAS data set also provides department level control variables. Demographic control variables have been obtained from the U.S. Census.

Moreover, UCR Data, LEMAS Data for available years (1997, 1999, 2000, 2003), and Census 2000 Data have been pooled together in order to create a panel of data for police departments over time. Although there are gaps in the availability of data for each year this has been considered as a necessary limitation as no other data sets are available for that purpose.

In order to measure the diffusion of crime mapping use across time and space, variables measuring time of the technology adopted and geographic location identifiers of the adopters are necessary for Chapter 3. CCMLE data set includes necessary variables to measure diffusion of crime mapping technology among police departments in the U.S. Also Census website provides place (city, township etc.), county, and state level maps for
geographical analysis.

Studying the impact of crime mapping on decision-making, specifically on police manager’s information based decision-making requires measures of crime mapping use and information provided by crime mapping technology, along with measures of managerial decision-making. In that sense, for the purposes of Chapter 4, CCMLE data set provides those measures.

In addition to all those data sets that contain necessary explanatory and dependent variables for data analyses, an additional data set was used in order to combine the key data sets. Law Enforcement Agency Identifiers Crosswalk [United States], 2000, which was created by the United States Department of Justice, Bureau of Justice Statistics, enables researchers to analyze crime and law enforcement data at the individual agency level by including unique key identifiers of various data sets into one data set. By putting together the Originating Reporting Agency Identifier (ORI) code, which is the unique case identifier in UCR data, with the agency identification (Agency ID) number, which is the unique case identifier in LEMAS data set along with other case identifiers such as zip code, Federal Information Processing Standard (FIPS) codes at county and city levels, and other similar government identification numbers, this data considerably shortens and eases the merging process.

**Case Selection**

While most of the police departments that responded to LEMAS, UCR or CCMLE data set are either municipal police departments at city level or sheriff’s offices
or county police departments at county level, there are other department types as well. Other types of police departments such as campus security, housing authority, natural resources preservation, wildlife parks, highway safety units, state patrols, airport police etc. were excluded from the data set since these departments do not serve regular populations and thus lack measures on demographics. Also general county police departments that are responsible for the same jurisdictional area with a sheriff’s department that is present in the data set were also excluded from the data set to prevent duplicate cases.

Data Sets

Uniform Crime Reports

UCR is a data collection effort designed to provide an overall view of crime in the U.S. Data for the UCR have been gathered by the Federal Bureau of Investigation (FBI) since 1930 from city, county and state law enforcement agencies. Reports for data gathering purposes are sent out and collected on a monthly basis. Due to the vast number of categories of crime committed in the U.S., the FBI has limited the types of crime included in this compilation to those crimes which people are most likely to report to police and those crimes which occur frequently enough to be analyzed across time.

The UCR reports clearances for two major offense categories: Part I offenses, including violent personal and property crimes – murder, rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, and arson (these offenses are often referred
to as Index Crimes) – and Part II offenses, that include other types of crime (drug offenses, sex offenses, fraud, weapons offenses, prostitution, disorderly conduct etc.) (White, 2007, p. 212).

The most important criticism made against UCR is the “Hierarchy Rule,” which entails elimination of other offences apart from the most serious one in a multiple offense case (Hagan, 2003). The original design of the summary-based UCR program designates criminal homicide as the most serious offense followed by rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft in order of seriousness. So, in an incident that involves both larceny and aggravated assault, only aggravated assault is counted, which is a limitation on the usefulness of the UCR data for understanding the nature of some crime types (Faggiani & Hirschel, 2005, p. 102). Another methodological issue about use of UCR is that each act is listed as a single offense for some crimes but not others and incomplete acts are lumped together with completed ones (Siegel, 1997).

It is also very important to note that crimes as measured by the UCR are “crimes known to the police” as measured by criminal “events either reported to or observed by the police” (Inciardi, 1978, p. 4). Thus crime rates as measured by UCR is essentially a measure of citizens’ willingness to report crime and not necessarily a measure of actual levels of crime, most of which are not reported to the police or not observed by the police. In that sense, the measure of crime rates in UCR is not an appropriate measure of actual crimes.

UCR does not have many alternatives and among those alternatives only the National Incident-Based Reporting System (NIBRS) is an adequate enough data set for
the purposes of this study. However, the complexity, multiple record structure, unit of
analysis and logical relationships among records and fields (Maxfield, 1999, p. 133),
which make it almost impossible to merge it with police department level data sets are
the key reasons for preferring UCR over NIBRS. While the unit of analysis in UCR is
departments, the unit of analysis in NIBRS is incidents. In order to merge NIBRS
with police department level data, the process requires a conversion of the NIBRS’
incident units into departments, which is a tedious course and results in loss of a
considerable amount of cases. When it comes to other potentially useful data sets, Levitt
(1998) shows in his study about the relationship between crime reporting and the number
of police that UCR, National Crime Victimization Survey (NCVS) and National Crime
Survey (NCS) data sets all have reporting/recording bias and the magnitude of the biases
presented in those data sets are roughly similar.

Despite all the criticisms against UCR, the existence of clearance by arrest for
index crimes (criminal homicide, forcible rape, robbery, aggravated assault, burglary,
larceny-theft and motor vehicle theft) in the data set makes the data set an asset both for
its capacity to address the questions raised in the study and its availability to be combined
with other department level data sets. There are no other data sets available for a
representative sample of the police departments across the U.S. (Inciardi, 1978) and for
the purposes of this dissertation UCR is a good measure of crime clearances in the
jurisdictional areas of the police departments.
**Law Enforcement Management and Administrative Statistics**

LEMAS survey begun in 1987 in order to periodically collect data from State and local law enforcement agencies. All agencies employing 100 or more sworn personnel are included (e.g. LEMAS 2003 survey includes a total of 955 law enforcement agencies in the United States with 100 or more sworn officers determined as of June 30, 2000), as well as a representative sample of smaller agencies including all state and local law enforcement agencies that are publicly funded and employ at least one full-time or part-time sworn officer with general arrest powers. The unit of analysis for the data is the police departments. The survey includes several sections; census information, personnel, community policing activities, computers and information systems, operations, equipment and policies and programs.

**Use of Computerized Crime Mapping by Law Enforcement**

Mail surveys of police departments is one of the most widely used tools in criminal justice studies and one identified problem with survey data is the problem of objectivity with the measures. The validity of the responses in terms of the degree to which they reflect reality is questioned, since even representatives of the same police department might disagree on basic issues of whether or not a certain program or technology has been adopted by their agency (Skogan & Hartnett, 2005; Weiss, 1994).

CCMLE data is a fairly reliable and valid measure of crime mapping use in police departments since the main theme of the survey is crime mapping and the questionnaire was submitted directly to the officer who would be able to fill in the questions most
reliably (Weisburd & Lum, 2005). The survey includes very specific questions as to the versions of the software installed for crime mapping, technical specifications for the hardware used, the types of techniques employed and tools utilized. In that sense, it seems highly unlikely that a department that does not use crime mapping would report that they are using crime mapping.

CCMLE data set was created based on a nationwide survey of 2,004 police departments in the U.S. conducted during 1997 and 1998 by the Crime Mapping Research Center of the National Institute of Justice in order to determine which agencies were using geographic information systems, and to understand law enforcement agencies' use and knowledge of crime mapping (Mamalian & La Vigne, 1999). The sampling method and unit of analysis of this data set is the same with LEMAS data including all agencies with 100 or more full-time sworn officers and disproportionately sampling sheriff’s offices and special police.

With a 72% response rate, the data set includes specific questions about how long the agencies have been doing crime mapping, the tools and methods employed by the agencies, specifically the hardware and software used to do crime mapping and limitations to and problems of employing the technology for the purposes of the departments. This data set enables researchers to study temporal, institutional, spatial and resource-based use of crime mapping.

To the best of the author’s knowledge of the literature, this data set has not been subject to advanced and complicated statistical analysis beyond descriptive statistics of the characteristics of the police departments that use crime mapping since agency
identifying variables are not publicly available due to confidentiality concerns of the responding agencies. Since the publicly available CCMLE data set does not contain a case identifier variable that makes it possible to merge this data set into other police department level data sets, the complete data set including unique identifier variables was requested for restricted use from the Inter-university Consortium for Political and Social Research (ICPSR) – National Archive of Criminal Justice Data (NACJD). The request was granted and the most important variables – key geographic identifiers of the responding police departments – were obtained.

Census Data

The CENSUS data is the official population census of the U.S. which is conducted every ten years. During each Decennial census, the U.S. Census Bureau collects data from every household in the U.S. and its territories including demographic information. The CENSUS data were obtained from CENSUS Long-Form using geographic identifiers, population I, population II, housing I and housing II displays at both county and city levels.

The variables obtained from the CENSUS data are crucial in establishing theoretically correct and viable models in testing relationships between police inputs and police outputs since most crime theories make assumptions based on demographic properties of individuals or more aggregate level units such as neighborhoods. Thus, demographic characteristics have a strong explanatory power on crime and correlates of crime. Demographic changes account for most of the variation in shifting crimes,
decreased victimization, trends in offending and overall crime patterns (Fox, 2000).

On the other hand, demographic characteristics such as age, gender, race, income, marital status, education, employment status, and occupation are important correlates of crime since these demographic “attributes carry with them shared expectations about appropriate behavior and structural obstacles that both enable and constrain one’s behavioral choices”, which in turn lead to established daily patterns of routine activities that might increase or decrease risk or being a victim of a crime as a result of exposure to risky situations within the routine (Miethe & Meier, 1994, p. 32).

**Data Merging Process**

I have created two data sets and two maps in order to conduct the statistical analyses in this research by merging the data sets explained above. The first data set is used for cross section analysis. The second data set is a merged panel data set. The first map includes all place level (city, township and municipality) police departments and the second map includes all county level police departments. Both merged data sets have been created through several tedious stages. During the merging process of both the data sets and the maps, I have encountered many technical difficulties that I was not able to solve using statistical software commands and had to do merging by hand. I do not want to articulate the detailed merging processes here but for future reference I have included a journal for the merging process in Appendix 2.
Conclusion

This chapter established the research objectives and research questions, as well as the measures used in this dissertation. Since the measures used in this study comes from different data sets, brief explanation as to the data sets and the data merging process has been given.

Consequently, this research examines three different themes on crime mapping and crime analysis based on a unique data set that is a combination of some well-known data sets, which are widely used in the criminal justice literature.
CHAPTER 3

DIFFUSION OF CRIME MAPPING IN THE UNITED STATES

Introduction

Policing has never been transformed so profoundly by anything else but technological advances and most of these changes have had their most substantial effect in the twentieth century (Ericson & Haggerty, 1997; Stroshine, 2005). While the availability of the police via telephone, which provides access to the community; communication among police officers via radio, which provides easier dispatching and deployment services; and patrolling by a car, which ensures rapid response and enables covering vast beats can be listed as the main paradigm shifts in policing in the early twentieth century. The most influential technological advance in the second half of the last century and at the dawn of the twenty first century, however, was advanced information technology (IT) and its adaptations in policing (Stroshine, 2005). Information processing technologies have changed the way police approach the phenomenon of crime, crime prevention and crime solving.

Recently, however, there has been a dramatic increase in demand among America's law enforcement community for better tools to track and anticipate criminal behavior, mostly due to the recent incidents of terrorism; other factors have contributed as well, such as the introduction of more powerful, analytical software and related
hardware and the willingness among government agencies to share and standardize data.

The number of police departments that use computers in a vast array of everyday activities ranging from painless record keeping to complex resource allocation strategies and complicated crime pattern detection and sophisticated analyses have increased rapidly.

Advanced technological tools such as crime analysis and crime mapping to fight crime are widely used in most police departments across the U.S. However, the spread of using crime mapping across the police departments is rarely studied. A better understanding of the diffusion of crime mapping across police departments in time and space will first of all enhance our knowledge of the diffusion of innovation and also enable us to predict patterns of how police technologies spread. More broadly, an understanding of how new technological innovations find their way into the problem solving activities of police departments will help us develop, particularly for public sector organizations, a theoretical understanding of the processes of innovation and diffusion and also provide us with an understanding of promoting productivity change at the local level.

In this particular chapter of the dissertation, I explain the temporal and spatial diffusion of crime mapping among police departments across the U.S. The chapter opens with a thorough literature review on the definition, attributes, and phases of the diffusion of innovation process. After examining the diffusion process of crime analysis across police departments in the U.S. in light of those attributes and phases, I describe the theoretical framework. The hypotheses are stated before the statistical analysis, which are
followed by the conclusions.

**Diffusion Process**

“A useful typology of technological change is provided by the Schumpeterian trilogy: invention (the generation of new ideas), innovation (the development of those ideas through to the first marketing or use of a technology) and diffusion (the spread of new technology across its potential market)” (Stoneman & Diederen, 1994, p. 918). In policing literature invention and innovation of police technology are frequently studied; diffusion of technology in policing, however, has hardly drawn much attention.

Diffusion is defined by Leichter (1983, p. 223) as “the process by which ideas, practices, and material objects spread across specified units of analysis” and by Lingamneni (1979, p. 18) as “the process by which innovations spread to the members of a social system.” Both definitions describe a gradual adoption of something new across the same or at least a comparable level of analysis. Rogers (2003) adds another interesting dimension to the above mentioned definition and notes that innovations are communicated through certain channels in a social system. Yet another broad definition of diffusion is provided by Katz, Levin and Hamilton (1963, p. 240) who characterize the process of diffusion by “the acceptance, over time, of some specific item – an idea or practice – by individuals, groups, or other adopting units, linked to specific channels of communication, to a social structure, and to a given system of values, or culture” [emphasis in original].

In that sense, diffusion is defined in this study as the process by which crime
mapping technology is adopted across police departments in the U.S. The diffusion theory (Stoneman & Diederer, 1994) can be adapted to the spread of the police use of crime mapping in such a way that the process is characterized by increases over time in both the number of police departments using or owning crime mapping technology (inter department diffusion) and more intensive use of the crime mapping technology by the department (intra department diffusion).

Diffusion of innovation in time across entities is argued to follow a common pattern and this pattern is often termed as the “s curve” or the sigmoid curve of diffusion of innovations (Grubler, 1996; Rogers, 2003). The curve suggests that initially the entities are reluctant to adopt the new technology and initially there are few adopters. Later the number of adopters increase and after some time there is a sharp increase in the rate of adoption. After a period of peaking, the rate of adoption slows and plateaus.

Depending on where they are placed on the curve adopters are classified into groups of innovators, early adopters, mainstream adopters (early majority and late majority), laggards, and resisters (Skogan & Hartnett, 2005) as shown on Figure 1. At first few entities are expected to embrace and test the new technology and these are referred to as innovators. Their followers are termed as early adopters. Mainstream adopters follow early adopters and are more cautious in adoption. Those that fail to adopt even after innovations become dominant are referred to as laggards and those reject to adopt the innovations are termed resisters.
According to Rogers (2003, pp. 15-16) the rate of adoption is affected by certain attributes of innovations and innovations with these attributes spread more quickly than others. An understanding of those attributes helps us recognize the differences in diffusion processes of different innovations;

- Relative advantage (Is it better than what was done before?)
- Compatibility (Is it consistent with values and beliefs and what was done before? Does it meet a felt need?)
- Complexity (Is it perceived as easy to understand and use?)
- Trialability (Can it be experimented with on a limited basis?)
- Observability (Are the results visible to others?)

Probably the only studies on the diffusion of crime mapping technology across police departments in the U.S. are by Weisburd and Lum (2005) and Chamard (2003).

---

1 Adopted from Rogers (2003, p. 281)
The authors have descriptively shown that the diffusion of crime mapping technology across police departments follows the common pattern of diffusion of innovation and creates a sigmoid curve over time based on limited local level surveys. They did not however, explore the reasons behind the fast adoption of crime mapping technology due to lack of data, nor did they discuss the spatial diffusion or the neighborhood effect of crime mapping technology.

The literature on the diffusion of technology essentially tries to explain why a new technology that is better than an old technology is not adopted instantaneously by all potential adopters (Curlee & Goel, 1989). Despite the fact that police departments are resistant to change (Lingamneni, 1979), crime mapping technology was swiftly welcomed among police departments. Rogers (2003) notes that more than benefits is necessary for an innovation to diffuse and to be accepted. There are two generally accepted answers to the question of why adoption occurs in the policy adoption literature. Internal determinants models hypothesize that the factors leading organizations to innovate are political, economic, and social characteristics of the environment, whereas regional diffusion models underline the influence of nearby organizations, assuming that organizations follow their neighbors when confronted with problems (F. S. Berry & Berry, 1990).

**Diffusion Process of Crime Mapping**

Police departments are infamously resistant to change, particularly change in police technology including crime analysis and crime mapping (White, 2007). While
some innovations such as radio communication are swiftly adopted (Harris, 2007), other technological advances such as integrated criminal justice information systems and crime reporting systems like the National Incident-Based Reporting System (NIBRS) have slowly been accepted within law enforcement community despite the potential benefits (Dunworth, 2005, p. 11).

Despite the reluctance of police to adopt new technologies, police departments around the U.S. are learning that the next generation crime analysis and crime mapping systems have a number of real-world advantages in their fight against crimes. By giving officers and supervisors the ability to pose their own queries, intelligence can be generated through more readily available information, information is disseminated faster, new insights are gained, and crimes have a better chance of being solved or even stopped before they occur (Astler, 2002).

**Adoption of Crime Mapping in the United States**

As suggested in the diffusion of innovations literature the diffusion of crime mapping across the police departments in the U.S. also follows a sigmoid curve with few initial adopters and a sharp increase in the number of the departments that embrace the technology following the pioneers. This effect is clearly shown in Figure 2. This figure is a scatter-plot of the number of police departments that have adopted crime mapping technology and the year of adoption of the technology.
Adopters in Last Ten Years

<table>
<thead>
<tr>
<th>Data Source</th>
<th>Year</th>
<th>Number of Adopters</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCMLE</td>
<td>1993</td>
<td>90</td>
</tr>
<tr>
<td>CCMLE</td>
<td>1994</td>
<td>123</td>
</tr>
<tr>
<td>CCMLE</td>
<td>1995</td>
<td>161</td>
</tr>
<tr>
<td>CCMLE</td>
<td>1996</td>
<td>208</td>
</tr>
<tr>
<td>CCMLE</td>
<td>1997</td>
<td>252</td>
</tr>
<tr>
<td>LEMAS</td>
<td>2000</td>
<td>828</td>
</tr>
<tr>
<td>LEMAS</td>
<td>2003</td>
<td>923</td>
</tr>
</tbody>
</table>

Figure 2 Number of Mapping Departments Over the Years
The data for years between 1977 and 1997 in Figure 2 comes from the CCMLE data set, the data for the years 2000 and 2003 come from the respective LEMAS survey results. While the way the question of whether crime mapping is used in department is asked in a rather different way in CCMLE and LEMAS data sets, the LEMAS values are added to reflect the obvious sigmoid curve trend in adoption of crime mapping.

After 1990s, when crime mapping technology became more user-friendly and less expensive, there is an exponential increase in the number of adopters. Evidently, the process of crime mapping adoption is not as complete as the increase in adopters shown in Figure 2 still continues, and there still are many police departments in the U.S. that do not have crime mapping technology.

In Table 1, a comparison of innovators with later adopters is given. In the Table, police agencies that have adopted crime mapping between 1977 and 1988 are considered innovators and police agencies that have adopted crime mapping in later years are considered among early adopters and early majority. As explained above, the diffusion process of crime mapping innovation still continues, thus it would be too early to recognize and identify all departments that fall into the groups of innovators, early adopters, mainstream adopters, laggards, and resisters.

A comparison of the mean values of the attributes of the initial adopters and later adopters shows that there is not much of a difference between the two groups. It should be noted that there are only 19 police departments in the innovators groups and 233 police departments in the latter group. The minimum and maximum values suggest there is wide variation in terms of the given attributes in the innovators group. Based on the
variables in Table 1, innovators seem no different than later adopters. Still, a detailed examination of those cases, which is beyond the scope of this study, might reveal more information on initial adoption and innovativeness.

Table 1 Comparison of Innovators with Later Adopters

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>Total Crimes</td>
<td>5,564</td>
<td>10,965</td>
</tr>
<tr>
<td>Violent Crimes</td>
<td>470</td>
<td>1,228</td>
</tr>
<tr>
<td>Property Crimes</td>
<td>5,095</td>
<td>9,847</td>
</tr>
<tr>
<td>Total Clearances</td>
<td>2,934</td>
<td>7,308</td>
</tr>
<tr>
<td>Violent Crime Clearances</td>
<td>2,227</td>
<td>5,767</td>
</tr>
<tr>
<td>Property Crime Clearances</td>
<td>706</td>
<td>1,659</td>
</tr>
<tr>
<td>Population Density</td>
<td>3,259</td>
<td>3,393</td>
</tr>
<tr>
<td>Percent Sworn Officers</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Frequency of Crime Mapping Use</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

Based on the attributes of innovations suggested by Rogers (2003, pp. 15-16), I examine the swift rate of adoption of crime mapping below. Before discussing those attributes, however, we need to differentiate between classical methods of crime mapping and computerized crime mapping. Also a brief historical account of the development of the GIS is in order since the main focus of this part of my research is on the diffusion of computerized crime mapping, which is very different than classical methods of crime mapping.
The general meaning of crime mapping is the ability to understand the spatial nature of crime and crime locations using tools “consisting of hardware, software, data, people and organizations” by analytically processing relevant information through collection, storage, analysis and dissemination methods and techniques (Ratcliffe, 2004, p. 67). Crime mapping “achieved through the use of pushpins and a paper map” is a classical method of crime mapping that have been used for a long time, in fact, virtually since the police agencies have been established (La Vigne & Groff, 2001b, p. 203). Computerized crime mapping or desktop computer crime mapping refers to mapping activity that is achieved on desktop computers using specific software packages.

Foresman (1998, p. 11) recognizes five ages of GIS development. Characterized by primitive hardware and software, the Pioneer Age lasted from the mid-1950s to the early 1970s. The Research and Development Age lasted until the 1980s and was followed by the Implementation and Vendor Age, which lasted until the 1990s. The Client Applications Age of 1990s was followed by the Local and Global Network Age of today.

Crime mapping applications of GIS in policing started in the late 1980s and early 1990s, during the Implementation and Vendor Age, as desktop computing became cheaper due to falling costs and ready availability of more accessible and user friendly software. With improvements in desktop computer capacity, printer enhancements, and price reductions desktop computer crime mapping became an everyday, broadly accepted application in policing (Harries, 1999).
**Relative Advantage**

According to Rogers (2003, p. 15) “[r]elative advantage is the degree to which an innovation is perceived as better than the idea it supersedes.” He continues that convenience and satisfaction are as important factors for relative advantage as economic benefits. He also argues that perception of an innovation as advantageous is more important in the adoption decision than objective or real advantage.

Abrahamson (1991) also asserts that organizations rationally adopt technically efficient innovations that enable them to effectively and efficiently achieve their goals. When the demands of the environment in which the organization runs change and/or the technical and scientific knowledge about the subject matter of the organization advance, organizations adopt innovations that would help them bridge the gap between their goals and the changing conditions (Abrahamson, 1991).

In that sense, there is an obvious relative advantage in using computerized crime mapping over classical crime mapping considering the serious limitations of old pin maps in several aspects. While one might detect clusters of criminal activity visually with a paper map and pushpins (Canter, 1998, p. 160), old pin maps could not be manipulated or queried and they also lacked the ability to store data - as maps were updated previous crime patterns were lost (Harries, 1999, p. 1). Old pin maps are useful as long as several types of crime, usually represented by pins of different colors, are not mixed together (Harries, 1999, p. 1). With GIS, however, capturing, storing, manipulating, analyzing, displaying and querying geographic data and producing cartographic and statistical outputs is possible (Leipnik & Albert, 2003b, p. 3).
Nevertheless, computerized crime mapping have not always been as easy as it is nowadays with user-friendly desktop computers with easy-to-use interfaces. Back in the late 1960s and early 1970s crime mapping was possible only by using expensive and huge computer mainframes operated by experts (La Vigne & Groff, 2001b). These gigantic machines required intensive labor, first of all, in describing the boundaries of the map with numbered coordinates on punched cards, then in keypunching the cards, followed by a similar process of coding and keypunching to put the data on the map (Harries, 1999, p. 1). Few organizations could afford such luxury and until late 1980s and early 1990s only large police departments were likely to adopt the innovation (Harries, 1999).

*Compatibility*

Compatibility is defined by Rogers (2003, p. 15) as “the degree to which an innovation is perceived being consistent with the existing values, past experiences, and needs of potential adopters.” In other words compatibility is the harmony between what the innovation offers and the existing value system of the potential adopter. Innovations diffuse swiftly when they advance the goals of the organization considerably and fit the informal culture of the adopting entity (Wejnert, 2002).

As mentioned above crime mapping has always been used by police departments as part of their daily activity. Despite the change in methods and tools, the rationale behind computerized crime mapping is the same with classical crime mapping. The goal
of crime mapping is to visually detect patterns of criminal activity on a map of the 
jurisdiction and take informed action based on the mapping activity.

Criminological theories based on positivism, social ecology and the Chicago 
School also created awareness on spatial aspects of crime (Lersch, 2004). The spatial 
aspects of crime made crime prevention efforts such as situational crime prevention more 
space focused. Collective efficacy (Robert J. Sampson, Raudenbush, & Earls, 2003), 
broken windows (Wilson & Kelling, 1982), community policing (Goldstein, 1987; 
Sparrow, 1999), and other community oriented and neighborhood focused ideas aiming 
to build stronger communities, enhance informal social control and improve 
neighborhood cohesion have shown the importance of geographic policing. As a result, 
hot spots policing approach became indispensable for daily police work, since the main 
goal of hot spots analysis is to detect high-crime areas that need special attention (Eck, 
Chainey, Cameron, Leitner, & Wilson, 2005). Moreover, recent research suggests that 
more police departments feel that crime mapping would be a valuable tool in fighting 
crime if implemented in their departments (Mamalian & La Vigne, 1999).

**Complexity**

While some innovations are easily understood by the members of the adopting 
social system and thus easily acquired, others can be highly complex and complicated to 
be easily comprehended. Hence, complexity refers to “the degree to which an innovation 
is perceived as difficult to understand and use” (Rogers, 2003, p. 16).
It is hard to disagree that the most important change the new age computerized crime mapping has brought is not its analytical advances but its easiness to use and user-friendly interface which makes it possible for most officers with some training to use those systems. As opposed to the labor-intensive, expertise required crime mapping systems of the past, desktop computer crime mapping systems have automated geocoding processes and simplified interfaces that enables users with basic computer skills to conduct their own analyses and run their own queries in a matter of moments (Chainey & Ratcliffe, 2005).

Nonetheless, while the accounts above appear to paint a rosy picture for the diffusion of easy-to-use crime mapping hardware and software, many mapping applications require advanced skills and knowledge in cartography and GIS. The real value of computerized crime mapping lies in its ability to run complex analyses on spatial and temporal patterns of crime not in digitalizing paper maps with fancy pushpin icons. Thus, if the most is to be made out of crime mapping, the departments should train their personnel on how to better analyze crime mapping data, which can prove to be a matter of complexity.

Crime mapping is believed to enable officers to detect and recognize “problems underlying concentrations of the icons marking crime incidents” (Skogan & Hartnett, 2005, p. 416); however this might even turn out to be a particularly hard task for inexperienced and untrained officers. Consequently, crime mapping adoption might be unlikely for departments that are not ready in terms of resources due to its potential destabilizing effects. Because of the expertise and skills required by crime mapping,
police departments that adopt crime mapping need to either hire analysts or invest in training of current officers. If neither path is taken and the existing computer and analytical capabilities of the officers is relied upon, this would adversely affect the efficiency and effectiveness of crime mapping.

**Trialability**

Rogers (2003, p. 16) defines trialability – or testability as expressed in earlier versions of his book – as “the degree to which an innovation may be experimented with on a limited basis.” Trialability provides the potential adopter with an opportunity to try the innovation sort of in a trial and error method.

Obviously, partial testing of whether crime mapping can be or should be implemented in a department is an exclusive luxury for larger police departments with bigger budgets, more personnel that can be spared for testing and training. However, when the fact that almost 90 percent of all police departments across the U.S. are considered small law enforcement agencies that serve populations less than 50,000 (Paulsen, 2003), the importance of trialability in adoption of crime mapping can be better understood. Even with the considerably reduced cost and more user-friendly interfaces of new crime mapping technologies, small departments with fewer resources in terms of dedicated personnel and relatively low budgets are less likely to test or try crime mapping, simply due to implementation obstacles.
**Observability**

“Observability is the degree to which the results of an innovation are visible to others” (Rogers, 2003, p. 16). The more visible the results of an innovation, the more likely that it will be adopted. The results of crime mapping have two kinds of visibility. First, the actual products of crime mapping activities are visual. Unlike other policing strategies or analyses detecting crime patterns or hot spots on a map is a visual process. Thus the observability effect of crime mapping increases when what the police already knows or have a hunch for is analytically and visually proved on a map.

The visual results of small experimentations of crime mapping by individual members of the police organization are more likely to be appreciated by others in the organization and the innovation is more likely to be adopted. This reinforcement effect or prior innovation-decision is referred to as contingent-innovation decisions by Rogers (2003, p. 403).

The second is observability of success stories or best practices. Sometimes organizations prefer to delay adoption and until others who have adopted an innovation have achieved positive results as a result of accepting the innovation. Most police departments nowadays publish their success stories over the Internet or by other means by issuing crime maps in their jurisdiction. This clearly has an effect on other departments’ decision to adopt crime mapping. Likewise other communities are likely to impose such a change with their police.
Theory and Hypotheses

Spatial Diffusion

Although time is an important aspect of diffusion since, after all, diffusion is essentially a temporal process; the main focus of this study is on the spatial aspect of diffusion since temporality is only one side of the explanation.

Time is important in explaining the diffusion process at two points. First is in explaining, identifying and differentiating between adopters and their position on the adoption curve as explained above. Second is in explaining the decision making process for the innovation adoption. From the initial exposure to an innovation’s existence to the stage of continuance, Rogers (2003, p. 169) identifies five stages of the innovation-decision process; (1) Knowledge – awareness of the innovation, (2) Persuasion – forming an attitude about the innovation, (3) Decision – the choice to adopt or reject innovation, (4) Implementation – putting the innovation into use, and (5) Confirmation – reinforcement for the innovation decision.

In his extensive review of the diffusion of innovations literature, Abrahamson (1991) cites several studies that hypothesize that organizations are influenced in adoption of an innovation by other organizations that are geographically closer. In fact, despite the changing nature of the innovation process and the likelihood that “innovative activities could be geographically fragmented by the use of advanced information technologies” geographical proximity still remains as an important factor in organizations’ ability to stay up to date and innovative (Sonn & Storper, 2008, p. 1035).
Because of proximity people develop more social contacts and interact more with their neighbors and thus have more information concerning developments that occur close to them and have less information concerning developments that occur farther. In that sense, people are more likely to adopt an innovation that has been adopted by a closer person than one that has been adopted in a distant place (Hägerstrand, 1967).

Figure 3 Graphical view of Diffusion of Innovation Theory (Adapted from: Rogers, 1995).

When we compare the departments that use crime mapping with departments that do not, several aspects are highly significant. As seen on Table 2, where a comparison of departments has been made based on certain characteristics, there is a significant
difference between adopters and non-adopters in terms of crime rates. There also are differences in demographic characteristics such as percentage of population living in urban areas, percent below poverty, population density and total population. The figures in Table 2 are based on a t-test comparing the mean values for the attributes of the police departments.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Violent Crimes</strong></td>
<td>113.62</td>
<td>33.78</td>
<td>137.53</td>
</tr>
<tr>
<td><strong>Property Crimes</strong></td>
<td>1686.05</td>
<td>864.32</td>
<td>1222.76</td>
</tr>
<tr>
<td><strong># of Sworn</strong></td>
<td>2.00</td>
<td>1.77</td>
<td>1.21</td>
</tr>
<tr>
<td><strong>Urban Percentage</strong></td>
<td>93.17</td>
<td>66.34</td>
<td>17.40</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td>52.10</td>
<td>52.58</td>
<td>8.26</td>
</tr>
<tr>
<td><strong>Below Poverty</strong></td>
<td>13.31</td>
<td>12.07</td>
<td>6.53</td>
</tr>
<tr>
<td><strong>Population Density</strong></td>
<td>3183.37</td>
<td>1536.70</td>
<td>3318.78</td>
</tr>
<tr>
<td><strong>Total Population</strong></td>
<td>358702.3</td>
<td>70857.21</td>
<td>713319.7</td>
</tr>
</tbody>
</table>

Equal variances were assumed in the calculation of the t-statistics
* Significant at .05 level
** Significant at .001 level

In order to study diffusion of crime mapping across police departments, I use the theoretical framework provided by innovation diffusion literature laid out in this chapter. The theoretical framework here mainly builds upon the paradigm developed in the works of Rogers (2003) for an understanding of how new ideas and technologies spread among a population. Based on the theoretical framework created by Rogers (2003) the reasons behind the fast adoption of crime mapping technology in police departments across the U.S. will be discussed and, if it exists, the spatial pattern to this diffusion will be empirically tested.
As to the spatial diffusion of crime mapping across police departments in the U.S., the regional diffusion model advanced by Walker (1969) will be used. Walker (1969) basically argues that the diffusion process can be visualized within a geographical pattern on a map. He identifies initial adopters as regional pioneers and argues that others follow regional pioneers by taking cues from them.

The figures 4 to 12 below visually show the diffusion of crime mapping among police departments across the contiguous United States.²

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² In order to increase visual clarity Alaska, Hawaii and all off-shore U.S. territories were excluded from the maps.
Figure 5 Departments that use Crime Mapping - 1977 -1983

Figure 6 Departments that use Crime Mapping - 1977 -1985
Figure 7 Departments that use Crime Mapping - 1977 -1987

Figure 8 Departments that use Crime Mapping - 1977 -1989
Figure 9 Departments that use Crime Mapping - 1977 -1991

Figure 10 Departments that use Crime Mapping - 1977 -1993
Figure 11 Departments that use Crime Mapping - 1977 - 1995

Figure 12 Departments that use Crime Mapping - 1977 - 1997
Figure 13 All Departments that use Crime Mapping based on Regions

The main research question in this part of the study is whether there is a spatial pattern to diffusion of crime mapping technology among police departments in the U.S.

The hypothesis derived from the research question is that the police departments that adopt crime mapping technology are geographically clustered across the U.S.

Methodology

There are multiple methods that enable researchers to detect recognizable geographical patterns. In order to test the hypothesis stated above, quadrat analysis, nearest neighbor analysis, and spatial autocorrelation coefficient can be used.

Quadrant analysis “evaluates a point distribution by examining how its density changes over space” usually by comparing the distribution obtained from the analysis to a theoretically constructed random pattern to measure clustering or dispersion (Lee & Wong, 2001, p. 62). Likewise, the nearest neighbor analysis “compares the average distance between nearest neighbors in a point distribution to that of a theoretical random
pattern” (Lee & Wong, 2001, p. 59). On the other hand, “the spatial autocorrelation coefficient measures how similar or dissimilar an attribute of neighboring points is” (Lee & Wong, 2001, p. 59).

Quadrant analysis is not appropriate to test the hypothesis in this research since this analysis looks at the number of points within a grid and detects whether the distribution of points within the grid is clustered, random or dispersed. However the distance between the points is not taken into account. When counties and cities are studied distances are very important. Compare two spatial configurations in Figure 14. While both configurations yield the same results with Quadrant analysis, there is a visual difference between configuration (a), which looks dispersed and configuration (b), which looks clustered. In order to distinguish patterns in such cases, nearest neighbor analysis is used.

![Figure 14 Local Clusters with Regional Dispersion](image)

Figure 14 Local Clusters with Regional Dispersion

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3 Adapted from Lee & Wong (2001, p. 69).
Spatial autocorrelation distinguishes the points by their attributes. If the researcher is interested in detecting a pattern, where geographical objects of interests with similar attributes are clustered together, spatial autocorrelation must be used since this analysis, unlike quadrant or nearest neighbor analysis, allows the researcher to use continuous variables in the analysis (Lee & Wong, 2001). In this study the attribute of interest is not continuous and for the purpose of this research average nearest neighbor analysis will be used.

In order to test the hypothesis regarding the spatial diffusion of technology, average nearest neighbor analysis will be conducted on ArcGIS mapping software. CCMLE data set includes a variable measuring the number of months the police departments have been doing crime mapping.

In their descriptive study on the diffusion of crime mapping innovation across police departments in the U.S., Weisburd and Lum (2005) point out an important limitation of this variable, that is, it is not possible to determine exactly when a recent adopting department began using crime mapping since the dates of survey completions are not recorded. This creates the problem of not determining at what point the department answered the question of how many months ago they started using crime mapping during the course of the survey administration, which lasted about fifteen months between March 1997 and May 1998.

In order to solve this problem the authors considered the mid-point of the survey administration period as the date of adoption for departments that reported to have started using crime mapping in the last 12 months. The same method is adopted for this study.
The key variable for crime mapping adoption, as measured by the year since the department has been doing crime mapping, was obtained from the data set by taking September 1997 as the completion time of the survey and subtracting the number of months the department have been doing crime mapping.

Based on that variable, on which year the departments adopted crime mapping technology can be determined. The crime mapping starts with the earliest adopter in 1978. CENSUS Data based location identifiers and maps are available for each police department, which makes spatial analysis possible since we have both the time and location variables.

**Average Nearest Neighbor Analysis and Findings**

Average nearest neighbor analysis “measures the distance between each feature centroid and its nearest neighbor’s centroid location. It then averages all these nearest neighbor distances” (ESRI, 2007) and calculates a statistic. If the calculated nearest neighbor statistic is below the threshold for “a hypothetical random distribution, the distribution of the features being analyzed are considered clustered”; if, on the contrary, the statistics is above the threshold for “a hypothetical random distribution, the features are considered dispersed” (ESRI, 2007).

Therefore, the nearest-neighbor statistic $R$, sometimes called the R-scale, is a measure of randomness in geographical patterns and is calculated using the formula (Lee & Wong, 2001, p. 72) given in Equation 1, “where $r_{obs}$ is the observed average distance between nearest neighbors and $r_{exp}$ is the expected average distance between nearest
neighbors as determined by the theoretical pattern being tested” (Lee & Wong, 2001, p. 73).

\[ R = \frac{r_{obs}}{r_{exp}} \]

**Equation 1 Nearest-Neighbor Statistic Formula**

Possible values of the R scale range from \( R = 0 \) (maximum clustering) to \( R = 1 \) (random pattern) to \( R = 2.149 \) (maximum dispersion) (Rossbacher, 1986, p. 102). The following figure (Figure 15) illustrates the idea of clustering, randomness and dispersion over geographical patterns on the R scale.

**Figure 15 The Scale of R Statistics**

In order to test hypotheses with average nearest neighbor analysis, that is to test randomness of the R scale, standard errors (SE\(_r\)) are obtained. Standard error here represents the likelihood that the difference between observed average distance and the expected average distance is due to pure chance (Lee & Wong, 2001, p. 75). Once the

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4 The R statistic values given are for illustrative purposes only and do not reflect actual calculations but merely approximations. The figure is adopted from Lee & Wong’s (2001, p. 74) same titled figure and recreated accordingly using the United States map.
standard errors are obtained, a standardized z score ($Z_R$) is calculated using the following formula (Equation 2) in order to test whether the observed (Lee & Wong, 2001, p. 75) geographical pattern occurs purely by chance or by some identifiable fashion;

$$Z_R = \frac{r_{obs} - r_{exp}}{SE_r}$$

**Equation 2 Standardized Score Formula for R Scale**

Figure 16 illustrates the standard normal distribution and the percentage of areas under the curve based on deviations from the mean in z score values and standard deviations. With average nearest neighbor analysis z scores smaller than -1.96 shows significance at 95% statistical significance level, which shows that only 5 out of 100 times such a geographical pattern might occur randomly.

![Normal, Bell-shaped Curve](image)

**Figure 16 Standard Normal Distribution and Different Illustrations of Area under the Curve**

Two different methods were followed to test the hypothesis using average nearest neighbor analysis. In the data set used for the analysis there are two levels of police
departments, place (town, city and township) and county. When department level data are merged with the geographical data on the map, there are overlaps on the areas, which make the correct spatial analysis impossible. Therefore the departments, thus the data, were split into two maps. The first map includes only place level police departments. The second map includes only county level police departments, however, if a county has both no county level police department but one or more place level police departments within its boundaries, the place level department that have been doing crime mapping for the longest period of time has been left on the map to gain cases.

Based on the variable that measures the number of months the departments have been doing crime mapping, both maps were divided into cumulative sections to capture temporality. For each section average nearest neighbor analysis was performed. However, the analysis could not be completed for the departments at the early years of adoption since, as discussed previously in the chapter, there are very few adopters at the beginning following the sigmoid curve of innovations. Average nearest neighbor analysis gave error messages for the first five cumulative periods for both place and county level analyses due to insufficient number of cases to complete the analysis. Thus, although the earliest innovator started crime mapping in 1977, the analyses could be conducted on the last five cumulative periods beginning at 1987 (cumulative period of 1987 to 1997) and following biennially until 1995 (cumulative period of 1995 to 1997).

The simple logic behind splitting the data into periods is to see whether as time passes there is a significant spatial pattern to diffusion of crime mapping; in other words and in average nearest neighbor analysis terms, whether the departments that adopt crime
mapping significantly cluster together in terms of geographical proximity as time
advances.

The null hypothesis tested in this analysis is that the police departments that adopt
crime mapping technology are randomly distributed across the U.S.

\( H_0: R=1 \)

The alternative hypothesis, on the other hand, is that the police departments that
adopt crime mapping technology are clustered across the U.S.

\( H_A: R<1 \)

**Table 3 Average Nearest Neighbor Analysis Results**

<table>
<thead>
<tr>
<th>Periods</th>
<th>Place Level Police Departments</th>
<th>County Level Police Departments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R-scale</td>
<td>z-score</td>
</tr>
<tr>
<td>1987-1997</td>
<td>1.162953</td>
<td>1.033926</td>
</tr>
<tr>
<td>1989-1997</td>
<td>1.00272</td>
<td>0.022079</td>
</tr>
<tr>
<td>1991-1997</td>
<td>0.693317</td>
<td>-3.568797*</td>
</tr>
<tr>
<td>1993-1997</td>
<td>0.756493</td>
<td>-3.925289*</td>
</tr>
<tr>
<td>1995-1997</td>
<td>0.683519</td>
<td>-7.138151*</td>
</tr>
</tbody>
</table>

Z-scores marked with “*” signifies that the associated R-scale is significantly clustered.

Table 3 reports the results for the average nearest neighbor analysis for both place
and county level police departments over five cumulative periods between 1987 and
1997. As can visually be seen from the distribution of the police departments that have
adopted crime mapping on the maps in Figures 4 to 7, there are very few cases to run
analyses. In average nearest neighbor analysis, a z-score of -1.96 and smaller shows that
the features being analyzed are clustered. As the z-score gets smaller, the level of
clustering increases.
The analyses have shown that after 1991 until 1997 the distribution of the police departments that have adopted crime mapping has a clustered nature. For the cumulative period between years 1991 and 1997, the null hypothesis is rejected in favor of the alternative hypothesis. In other words, in those periods departments that adopted crime mapping significantly clustered across the U.S. For the cumulative periods, 1987-1997 and 1989-1997 the null hypothesis could not be rejected. That is, for these two periods the spread of crime mapping adopters is of a random nature without any identifiable spatial pattern.

**Conclusion**

The results of the average nearest neighbor analyses conducted on cumulative periods of crime mapping adoption by police departments across the U.S. indicate that departments that use mapping technology are significantly closer to each other spatially. In other words, geographically closer departments are more likely to adopt crime mapping technology.

The clustering that is visually obvious on the maps in Figures 9 to 13 and statistically shown by the spatial analysis conducted in the analysis section present evidence that, over time, the diffusion of crime mapping technology shows an identifiable and theoretically meaningful spatial pattern. To put in other words, geographical proximity matters in explaining the adoption of crime mapping technology by police departments.
CHAPTER 4

DECISION-MAKING AND CRIME MAPPING

Introduction

In this chapter, I develop an empirical test of whether departments that do more crime mapping use information obtained from crime mapping more in resource allocation and redistricting decisions. The contribution of crime mapping to decision-making will be discussed after a brief review of the relevant literature on decision-making of the police manager. Based on the empirical analysis of whether police departments that use crime mapping extensively base their resource allocation and redistricting decisions on information obtained from mapping, a normative argument will follow in the conclusion chapter under policy implications section about how decision-making can be further optimized and be more informed when based on information acquired from crime mapping analysis.

There is no question that police organizations play a particularly important and vital role in the quality of life of the members of the community. The decisions that police managers make can have significant effects on both the police organization and the society. Almost everyday police managers are required to make swift judgments and decisions that affect the lives and welfare of their subordinates and citizens that they have a duty to protect. Some decisions such as when to take a break or where the desks should
be located are simple decisions that have insignificant effect on others (Petrillo & DelBagno, 2001). Other decisions such as budget allocation, patrol type and districts, scheduling training schemes or formations to take while dealing with riot situations, however, are far more complicated and have significant effects on the officers and the police department (Petrillo & DelBagno, 2001).

Executives and managers of police agencies depend on making informed decisions to deal with crises and change occurring in their respective environments and their organizations. The key decisions made by these leaders are distinct from those on the spot decisions often made by law enforcement or correctional officers in in-field situations. In most instances, there is adequate time for police managers to reflect, assess, and collect additional data in order to make more informed decisions (Morreale, et al., 2003; Nutt, 1984).

Unlike line-level personnel, the relative position of the administrators often requires them to engage in strategic and long-term decision-making as opposed to crisis-driven decision-making of the street level decision makers. Thus, studying police managers’ decision-making is quite different from studying line-level personnel’s decision-making.

There is limited research available on police manager’s decision-making, including the area of informed decision-making in policing. However, this topic is quite important to benefit future and current police administrators. Some research on the decision-making of the police focus on the patrol officer as a problem solver (Cooper, 1997; Helsen & Starkes, 1999) and others focus on the line-level officer’s decision-
making and the proper use of discretion as an indispensable tool (Schafer, Carter, Katz-bannister, & Wells, 2006; Seron, Pereira, & Kovath, 2004). While some study the effect of perceptions of detectives and mid-level managers on decision-making (Corsianos, 2001), criminal justice researchers have paid scant attention to decision-making of the police manager and the various elements of effective decision-making processes. This important aspect of policing is equally, if not more, important to the future of the policing industry than street level decision-making of the patrol officers or detectives (Morreale, et al., 2003).

The primary focus in this chapter is on decision-making of the police manager based on analytical information, particularly information acquired from crime mapping. As already mentioned in the previous chapters, crime mapping in this study refers to collection, storage, analysis and dissemination of information relating to the spatial aspects of crime, employing tools consisting of hardware, software, data, people and organizations (Ratcliffe, 2004).

**Decision-making**

According to Inbar (1979), in order to fully understand “decision-making” as a term, one needs to look at the two different meanings of the word itself. One is goal setting, which involves the process of transforming aspirations and values into accepted social goals. The other is goal achievement, which specifically deals with the successful implementation of the goals into the process. Goal setting is typically seen as a sociopolitical process while goal achievement is more prone to problem solving.
Decision-making as used in this chapter mainly refers to goal achievement in terms of applying what has been learned from crime mapping to the implementation of organizational goals.

The main aim of goal achievement in decision-making is resolving problems or making choices. According to Gottfredson and Gottfredson (1988) there are three main components of any decision: goal, alternatives, and information. First, there must be a goal, an end, or a decision problem that the decision maker wants to overcome. Secondly, there must be some alternatives available. If there is no choice then there is no problem. However, decision-making is not as easy as it sounds and it is not simply picking up a choice randomly among multiple alternatives. Finally, the decision maker must have some information to guide the selections among various options. In order to qualify as information *per se* from a relevancy perspective, the data available must be related and pertinent to the goals of the decision.

In that sense, decision-making is a rational cognitive course of action by which a choice is made from several options. The task of rational decision-making is to choose one of the strategies which will be followed by the favored set of results (Ming-Yueh & Yun-Ming, 1993). The process of decision-making, however, is and should be more comprehensive and extensive than just making choices and simply picking alternatives. Decision-making involves taking into account the relevant and available information, processing the information in the context of the available resources, and selecting a course of action from two or more alternatives for accomplishing a desired result. There are three levels of decision-making that present themselves in police organizations. These
decisions fall into the domains of routine decision-making, crisis management and strategic management (Morreale, et al., 2003).

Routine decision-making involves daily and non-strategic decision-making and crisis management. As the term implies, crisis management is about decision-making in emergencies without time to effectively evaluate the alternatives or consequences. For the purpose of this study, the term, decision-making, refers to systematic and strategic decision-making, which includes collecting and evaluating information and data, giving other stakeholders the opportunity to review and provide input, and reviewing previous best practices in organizational decision-making (Power, 1983).

Strategic decision-making, as a context, allows for careful consideration, and reflection and involvement of stakeholders. In this context, it is imperative to have a systematic process of information gathering, discussion, review, consideration and weighing alternatives and an ongoing assessment. The quality, accuracy, and relevance of information, also, are critical in decision-making. Very often, individuals base their decisions on limited information and intuition. While this may be effective for the street level bureaucrats (i.e. patrol officers) and certainly plays a role in examining a minor issue, when organizational level decision-making is considered there are additional steps or methods that should be incorporated in the process (Morreale, et al., 2003).

There is not a fixed or a set pattern that individuals follow when making a decision. While some people want to evaluate, in a rational manner, all the information available, including consulting with others before making a decision; others prefer to take into consideration what they regard as the most important and vital issues. In this sense,
how managers eventually make decisions will be influenced by their personal characteristics and will influence the quality of their decisions (Worrall, Southerland, Angell, & Gaines, 2003).

Personal characteristics refer to the decision maker’s skills, scope of knowledge, idiosyncrasies, biases, and attitudes. Simon (1997) suggests that the limits on a manager include the limits on his ability to perform and limits on his ability to make correct decisions. According to him, performance may be limited by personal skills and this affects decision-making processes. The decision-making individual is bound with his values and the extent of his knowledge relevant to the decision to be made. The decision maker must be able to rationally analyze problems, situations and people so as to make the decision that best resolves the problem or the issue without being tainted by his personal and personality characteristics (Worrall, et al., 2003).

Nigro & Nigro (1980) identified two fundamental issues that put influences on managers during the decision-making process: outside pressures and personal characteristics. While outside pressures on decision-making are irrelevant for the purpose of this study, they certainly can have an impact on the decision-making process. Outside pressures refer to laws, people, and social, political, and economic conditions that impose limits and place constraints on the manager in terms of what is acceptable or feasible. State laws often restrict the police manager’s decisions and the manager generally has to decide based on policies, procedures, or regulations.

Personal characteristics can certainly affect the decision makers ability to process information, thus the processing of the information obtained from crime mapping will
differ from decision maker to decision maker based on individuals’ cognitive abilities, patience and fortitude. A successful decision maker can deal with those pressures on a continuous basis and is able to mediate, bargain and negotiate compromises in the best interests of the department and the community (Petrillo & DelBagno, 2001).

According to Leibenstein (1980) there are conflicting sides within an individual. One part of a person will want to satisfy a desire to do what he wants and another part will be bound with a set of internalized behaviors that have been learned. These two conflicting sides will eventually come to a compromise. He claims that individuals will make rational decisions based on maximizing efficiency and argues that many factors are involved in decision-making and an individual will compromise and settle for a comfortable level of constraint.

So far, the most obvious common aspect of decision-making discussed in the literature is the use of information during the process. While outside pressures and individual constraints might limit, shape, and affect the way and the manner the information is used in decision-making, decisions are eventually made based on available information. For police managers most of the information comes from departmental resources, analyses and reports. Thus, crime mapping information can be vital in making the optimum decisions since it is generally compact, to the point and comprehensive.

In that sense, there is an argument in the literature for rationality in decision-making based on taking information that is relevant to and required for the decision into account during the process. The more relevant information a decision maker has the
better the decision can be made since information can close the gaps in decision-making that individual and environmental limitations create.

In ideal decision-making, the decision maker is supposed to take all relevant information into account and “weigh and combine it appropriately” especially “when their decisions have significant consequences” (Dhami, 2003, p. 175). The decision-making literature is weak on answering the question of whether “decision-making effectiveness and efficiency [can] be enhanced through better structuring of information acquisition” (Saunders & Jones, 1990, p. 29). However, in optimal decision-making the key is to clearly identify what information and how much of it is needed to solve the decision problem (Reiter, 1957). When there is too much information, it becomes extremely difficult and at times almost impossible to take out the relevant information among them. Rationality of the decision maker, therefore, requires him/her not only to gather all relevant information from relevant sources but also “to find out just what constitutes minimal information required for decision-making” (Reiter, 1957, p. 339) within a reasonable amount of time.

Simon (1997) argues that even though decisions are made rationally there are limits on the rationality of the decision maker. Thus, the decision maker has limited or bounded rationality. Downs (1994, p. 75) lists limitations or bounds to rationality as: (1) each decision maker can devote only a limited amount of time to decision-making, (2) each decision maker can mentally weigh and consider only a limited amount of information at one time, (3) the functions of most officials require them to become involved in more activities than they can consider simultaneously; hence they must
normally focus their attention on only part of their major concerns while the rest remain latent, (4) the amount of information initially available to every decision maker about each problem is only a small fraction of all the information potentially available on the subject, (5) additional information bearing on any particular problem can usually be procured, but the costs of procurement and utilization may rise rapidly as the amount of data increases, and (6) important aspects of many problems involve information that cannot be procured at all, especially concerning future events; hence many decisions must be made in the face of some ineradicable uncertainty.

According to Lynch (1978) there are three principles and rules of decision-making. The first general principle is to make decisions even when not all of these decisions come out correct, since an effective manager will eventually be given credit for his ability to make decisions. The second rule is that once the decision has been made the decision maker should not continually be concerned about the decision and be committed to implement it. This rule does not say that once decisions are made they cannot be changed, but it asserts that the decision maker should be consistent so as not to make things worse by constantly worrying about the decisions. In cases where a completely new and more effective approach has been established or the original decision has been proven inaccurate, a shift in the decision is needed. The third rule asserts that the manager should not try to satisfy everyone by taking into consideration all of their judgments; rather, he should concentrate on the managerial responsibilities and organizational goals in order to make a sound decision.
The establishment of a rich and clear picture that demonstrates the link between the objectives the organization is trying to achieve and various alternatives that have to be implemented, is one of the key components of decision-making and this is realized by building a chain that links together the *means* and the *ends* (Lynch, 1978). According to Simon (1997) rational choices are made on a *principle of efficiency* which puts forth the characteristic of any action that attempts to maximize the achievement of certain ends with the use of scarce means. His model of rationality maintains that there are three essential steps in decision-making: (1) list all the alternative strategies, (2) determine and calculate all of the consequences to each strategy, and (3) evaluate all of these consequences in a comparative fashion.

Unless he or she can understand the quality or deficiency of the information generated, the decision maker cannot possibly discriminate among different sets of information. One of the key prerequisites of effective decision-making is to understand and use the available information in the decision process. Not all available information is of the same quality; therefore, the decision maker has to be selective in understanding, evaluating and using information (Samli, 1996). The purpose of analyzing information in decision-making is to reduce or remove uncertainty, which can be defined as the difference between the information processed and the information required to complete a task or as an inability to predict accurately what the outcomes of a decision might be (Frishammar, 2003).
Organizational Information, Crime Analysis and Crime Mapping

Organizations rely on information processing and problem solving for institutional survival and continuation (Arrow, 1974), thus for law enforcement organizations crime prevention and crime solving are, in essence, information processing and problem solving tasks. Therefore, most law enforcement agencies present information technology as support for their personnel at all levels (Gottschalk, 2007).

Contemporary criminal justice organizations are more and more dependent on the rapid and accurate collection, analysis, and dissemination of information in order to make decisions effectively and allocate resources efficiently. Recent developments in computer technology became vital elements of information management and decision-making in criminal justice organizations (Archambeault & Archambeault, 1989). The scope and nature of the work undertaken by police departments make it almost compulsory to collect, store and analyze data and base tactical and administrative decisions on strategic information extracted from the analysis of gathered data.

As in business and marketing sectors, information can enhance competitive advantage in the public administration sector, especially in police organizations. Just as accurate analysis and information processing make some businesses the leaders of their area, crime analysis can help police departments improve their capabilities in their incessant combat against crime and criminals.

Power (1983) argues that improved management of organizational information can have a revolutionary effect on organizations. He suggests that managers must contemplate the consequences of expanding information management activities since the
means are now available to implement sophisticated information systems. In this context, the number of police departments using computerized records management systems to store, analyze, and retrieve data has increased in recent years, as the police managers have better understood the need for data and information and how computers can serve their needs (Worrall et al., 2003).

Considering the thoughts advanced by Pope, Lovell and Brandl (2001) regarding the current role of information in decisions, the importance of reliable and strategic information becomes clear. Pope et al. (2001) suggest that decision makers must find specific research results to be so compelling that they base changes in programs and policies directly on the research information. Research and data may influence a decision, as opposed to dictating change. Decision makers may use the data or research to help guide or clarify policymaking. Decision makers may use the data and research to substantiate or legitimize a position or decision already arrived at, to refute or cast doubt on propositions advanced by others, to persuade or neutralize others, to buttress a request for funding, or similar purposes. Information acquired from crime analysis has the nature and capacity to guide decision makers in police organizations effectively.

One of the questions in decision-making is the role that knowledge, information (or intelligence) and analysis play in organizational decision-making (Gist, 1998). Managers who use information technology as a decision-making tool rated the use of computer based information the highest in supporting the final evaluation step in decision-making in a study by Vlahos and Ferratt (1995) about the use and the value of
and satisfaction with computer-based information in making decisions on planning, controlling and operating.

The potential of crime analysis and crime mapping, combining a technology and a technique, is greater than any other improvement in policing in recent years. This is due to the fact that they create positive images about the basic questions and contradictions in the literature – “that policing can control crime, reduce the fear of crime, and yet be an almost entirely responsive, demand-driven, situational force dispensing just in time and just enough order maintenance” (Manning, 2001, p. 101).

Managers, particularly in police organizations, are faced with the important duty of making crucial decisions under complicated situations and highly chaotic environments (Saunders & Jones, 1990). The decision-making models for managers generally focus either on the stage of information acquisition of communication or on the stage of use of the information in making decisions. However, even when a manager can make good use of information under various conditions, the managers’ capability of decision making is limited with the quality of the information. On the other hand, even when the information is of high quality the decision-making capability of the manager can limit the effectiveness and end the efficiency of the process. Since we cannot always find managers that have superb decision-making and analytic skills enhanced with foresight, we need to find ways to improve the quality of the information on which the managers base their organizational decisions.

To better illustrate the difficulty of managerial decision-making within a police organization consider the following example. Imagine a police chief who has newly been
recruited to the office by the city with hopes of decreasing crime rates in the community. The chief receives daily crime reports and statistics from his/her subordinates and is kept updated on each and every major investigation. In order to delve into the core of the problem the chief needs to draw a comprehensive rich picture of criminal incidents based on location, time, *modus operandi*, offender characteristics and organizational resources (whether patrolling is offered in that area or at that time).

When personnel problems, budgetary issues and other managerial tasks are added to this load, the decision-making capability of the chief significantly decreases. For a small city, this is a full time job, for a midsized or big city, this is practically impossible without the aid of computerized programs. If the chief can see the concentrated crime areas, hotspots for certain crimes, temporal and spatial crime displacements, patrol beats and other such useful information on a map of the city, his information generation and processing load would reduce significantly and he would be able to see the big picture mentally and visually. Now the chief can turn to other sources of information such as peer advice, best practices from other jurisdictions, and can make better decisions.

The information generated by crime analysis can lead to effective administrative and operational decision-making. Much of the time information that was converted from data must be very specific and to the point so that it will make sense in decision-making and be applicable in the practical area. For example, if the police chief is considering a change in patrol beats and assignment of patrol officers to crime laden areas, it is necessary for the information generated from crime mapping to indicate hotspots clearly by whatever criterion used (e.g. calls for service, number of burglaries) and enable the
chief to determine approximate beats in the area.

Use of effective crime mapping methods in order to determine hot spots of crime and map risk areas will provide the police agency the means to deploy patrol officers efficiently and thus avoid unnecessary labor and direct excess police forces to other areas where they are more needed. Crime mapping and crime analysis allow the police agency to draw inferences from patterns of crime that can be used as a basis for allocating police resources (Cope, 2004). However, the effective deployment of police resources, mainly the patrol officers, is heavily dependent on the quality of the analysis available (Townsley & Pease, 2002).

Goldstein (1990) noticeably demonstrates the critical relationship between data management and effective police work. In his normative decision-making model, Goldstein (1990) focuses on a rational, comprehensive search for the root causes of crime that is almost entirely information driven and he advocates for a system that places a high value on the gathering and processing of information from a variety of sources including crime analysis.

Crime analysis and crime mapping are the key tools in today’s world of enhanced technology to achieve the strategic level of knowledge, information and analysis in policing. Crime mapping, as a computerized information system, can potentially help the decision maker in several areas like problem finding, problem definition (identification), providing information regarding alternatives and selecting among alternatives (McGowan & Wittmer, 1998). There are five major payoffs of crime analysis and crime mapping in any aspect of police management and especially in decision-making; (1) increased
availability of information, (2) better information for management control, (3) better information for city planning decisions, (4) greater efficiency of operational performance, and (5) better interaction with the public (Northrop, Kraemer, Dunkle, & King, 1990).

The recognition of a problem is the first step in the decision-making process (Hoy & Tarter, 2004). The problem-finding area refers to the ability of crime analysis systems to search through and signal conditions that are out of the ordinary and exceptional. For example, an increase in the use of a certain type of a modus operandi in a particular type of crime can easily be detected with an analysis of crime data. Also, a concentration of a particular criminal activity in a certain area of the city can be determined with a crime mapping technique such as hot spots analysis, geographic profiling, or Geographic Information Systems (GIS) mapping (Eck, et al., 2005; Harries, 1999).

The problem definition stage in crime analysis and mapping goes beyond routine scanning and processing of data. When the nature of the issue of the problem is defined, the manager, as a decision maker, primarily uses the information in a support role. However, it is imperative to bear in mind that the information must be able to reduce uncertainty about the consequences of the problem and must be clear and explicit (Hoy & Tarter, 2004).

Let us presume that a crime analyst determined that a drastic increase in crime occurred in a particular neighborhood. After further analysis, s/he correlated the problem with the recent increase in migratory movements in the area. Now the police manager not only knows that there is an increase in crime in an area but s/he also knows a correlated reason for that. After recognition and definition of the problem, it is
imperative to analyze the situation and probe the nature of the identified problem by focusing on possible and potential solutions and alternatives. The answers to the questions of whether the problem is unique or whether it is a new manifestation of a routine difficulty or what patterns of action have been developed for similar problems in the past can guide the decision-making process (Hirschfield, 2001, p. 244).

High storage capacity of computerized systems allows these systems to have a certain kind of historical memory. What worked in the past for a certain problem under certain conditions can easily be traced and can be presented as an alternative course of action with reference to previous practice. The appropriateness of the past practices can be determined with a statistical comparison of the variables and conditions of the current and past situations. In this way, analysis helps the decision maker to see his/her alternatives along with the pros and cons and facilitates the process of decision-making for the decision maker.

Hirschfield (2001) identifies several specific applications that crime analysis can include, which are highly important in decision-making: (1) exploring relationships between crime and the environment, (2) identifying levels of crime in and around selected sites, (3) identifying mismatches between resources and needs, (4) providing information that will allow for the improved planning and allocation of resources for community safety and crime prevention work (targeting), (5) enabling the better coordination of services, (6) searching for evidence of spatial and temporal displacement of crime, (7) informing police operations against crime, (8) relating offence locations to those of previous offenders and known suspects, (9) communicating with and engaging
local communities, (10) supporting bids for extra resources from central government, 
(11) crowd control and traffic management, and (12) developing early warning systems 
of emerging problems.

In their study about the use of crime analysis in police departments in the U.S., 
O’Shea and Nicholls (2003) found that most departments utilize critical data (i.e., crime, 
arrests, calls for service and clearance rates) to some degree and that only about 5% of 
the departments in their study totally ignore these data. The number of departments that 
ignored traffic and citizen complaints was over 10%. The vast majority of the 
departments did somewhat utilize the data they collected. However, when the 
departments were asked how the data were utilized (whether the data are counted or 
analyzed) the results were interesting. Before asking the questions, the departments were 
advised that the term, “count,” was defined as keeping track of the number of 
occurrences. “Analyze” was defined as, in addition to counting, looking for trends and 
relationships in the data. Crimes and calls for service were analyzed by about 60% of the 
departments responding (66% and 56%, respectively). When it comes to arrests and 
clearance rates, less than 40% (38% and 33%, respectively) analyzed the data. A 
considerable number of departments, even in critical areas like crime and calls for service 
continued only to count data, rather than analyze the data for both decisional and 
operational purposes.

Geographic Information Systems (GIS) enable police managers to identify 
situational and environmental crime patterns and visually classify and categorize 
disconcerting and problematic clusters and spots of incidents (Jackson & Wade, 2005).
GIS can be a powerful tool for proactive policing due to its predictive capability. Proactive policing essentially is an effort towards solving crime problems by allocating resources in predetermined areas and neighborhoods (La Vigne & Groff, 2001a). By using hotspots analysis, for instance, police managers can use predictive models that identify future patterns of crime and indicate troubled areas to take preventive measures and deploy interventions beforehand (Vann & Garson, 2003). Hotspots analysis, a special case of GIS, helps the manager guide the allocation of resources by enabling the crime analyst to identify concentrations of crime.

Police departments, particularly those that employ computerized analysis tools potentially produce too much information due to the nature of the outputs generated by those tools. This information load and generally complicated data that come from different sources with various shapes and forms hides relevant information in the background. While information that police produce can be infinite, police resources are limited (Hirschfield, 2001). Crime mapping analyses are not flawless but the filtering capability of those systems enable the decision maker to sort out the information and extract relevant information that is hidden among huge loads of data.

A careful analysis of GIS data can yield crucial information on strategic geographical locations and hot spots of crime enabling the decision maker to pinpoint problematic areas within the responsibility area and take necessary measures (Vann & Garson, 2003). The ocular aspect of crime mapping can help the police manager share the information with his/her subordinates visually like a general deciding on a particular war
strategy with a model of battle fields rather than handling the issue based on abstract
discussions.

Crime mapping can improve departmental effectiveness at many levels. Police
detectives use crime mapping to track and trace serial crimes, patrol officers can be more
vigilant in areas of peaking criminal activity, mid-level police managers can allocate their
resources more efficiently and police department heads can make more informed
strategic planning decisions based on general crime trends (Hirschfield, 2001). For
instance, police managers, who are responsible for identifying strategic action plans and
priorities, can base their operational decisions on how to deploy their patrol officers on
information obtained from crime mapping systems (Leipnik & Albert, 2003b).

In that sense, as Leipnik and Albert (2003a) show, the police executive is another
typical GIS user. Unlike other users of GIS such as crime analysts, computerized crime
records management personnel, and patrol officers, police executives use GIS as a tool
for managerial, long-term, and strategic decision-making. Police managers can develop
enforcement strategies and even monitor personnel effectiveness based on crime
mapping.

Crime mapping enables decision-makers access to applicable, graphic information
on patterns, clusters and variables that were often out of reach with traditional and
obsolete crime analysis techniques (Vann & Garson, 2003). Acquiring information on the
intensity of certain crimes in certain areas is easier with visual aides of crime mapping
tools. For instance, tactical and strategic information on the proximity of crimes to
strategic premises such as schools, hazardous materials storage locations or other
community features can easily be obtained in relation to time, space and even weather patterns (Leipnik & Albert, 2003b).

The constant feedback and trend analysis in GIS generated information enables the decision maker to identify crime displacements, and thus redeploy resources accordingly and make necessary adjustments to previous decisions (Leipnik & Albert, 2003b). Another important aspect of displacement identification is the detection of concentrated crime at jurisdictional borders. A concentrated crime area can go unnoticed when criminal activities constantly cross borders or it can be ignored since it might never reach the critical level for any single jurisdiction. By pinning and highlighting both the problematic area and the jurisdictional boundaries, mapping helps decision makers detect those zones that spread over two or more jurisdictions and help coordinate efforts and required resources (Chainey & Ratcliffe, 2005, p. 9).

Consequently, decision-making is a critical and vital process in both short-term and long-term operations, and for practices and policies of police departments. In addition, as decision makers in those agencies, police chiefs have this important responsibility as a burden. Reliable and continuous information flow can remove this burden from the police chiefs and crime analysis can provide reliable information continuously when properly used and implemented. The power of GIS, for instance, can dramatically simplify the task of redistricting or adjusting boundaries in patrol areas, which normally is a time-consuming burden (R. A. Peterson, 1994).
Hypotheses

Based on the two distinct theoretical arguments discussed above, there are two main research questions in this part of the dissertation:

(1) Among departments using crime mapping, are those that produce more information based on various crime mapping activities more likely to use the information obtained from their crime mapping activities in their decisions to re-allocate resources and redistrict their beats?

(2) Among departments using crime mapping, are those that produce overwhelmingly more information based on various crime mapping activities less likely to use the information obtained from their crime mapping activities in their decisions to re-allocate resources and redistrict their beats?

In this section, I statistically test both questions based on the following hypothesis statements;

(1) Police departments that produce more information as a result of frequent use and employment of multiple analytical functions of crime mapping are more likely to use the information generated by crime mapping in resource allocation decisions than departments that produce minimal information. Also, police departments that produce more information as a result of frequent use and employment of multiple analytical functions of crime mapping are more likely to use the information generated by crime mapping in redistricting decisions than departments that produce minimal information.

(2) Police departments are likely to use the information generated by crime
mapping in *resource allocation decisions* to a certain extent; when they produce overwhelmingly more information as a result of frequent use and employment of multiple analytical functions of crime mapping they are less likely to use the information generated by crime mapping. Also police departments are likely to use the information generated by crime mapping in *redistricting decisions* to a certain extent; when they produce overwhelmingly more information as a result of frequent use and employment of multiple analytical functions of crime mapping they are less likely to use the information generated by crime mapping.

**Measurement and Methodology**

In order to test whether information obtained from crime mapping affects managerial decisions, limited dependent cross sectional analysis based on the CCMLE data, combined with CENSUS, LEMAS and UCR for the year 1997 will be used. The data set is the same combined data set that will be used in the effectiveness of crime mapping section and the merging process, which is explained in Appendix 2, is also the same.

The unit of analysis is police departments. The universe is all police departments in the U.S. The main limitation of the data set used here is the number of cases. In CCMLE data set police departments are divided into two main groups in terms of the questions they were asked to answer. If an agency used crime mapping in the department they were asked to complete sets of questions that are specifically related to use of crime
mapping, crime mapping techniques, software and hardware used and special applications. If an agency did not use crime mapping in the department, they were asked to skip the questions related to crime mapping use and complete a different set of questions related to computerized policing and potential inclination towards future adoption of crime mapping. Since the research questions articulated in this chapter specifically focus on decision-making based on crime mapping only the first portion of the CCMLE data set (police departments that use computerized crime mapping) will be used for the analysis in this Chapter.

In CCMLE survey, police departments that use crime mapping were asked whether they use the results of and information produced by crime mapping activities in resource allocation decisions and in redistricting of beats, reporting areas, etc. The dependent variables in this analysis are two dichotomous variables created from the aforementioned survey questions. The first dependent variable describes whether the information obtained from crime mapping is used in resource allocation decisions. The second dependent variable indicates whether the information obtained from crime mapping is used in redistricting decisions.

The main explanatory variable is the amount of information produced by the police department using crime mapping. This variable is a composite measure of the intensity and the type of crime mapping use. The intensity of crime mapping activities is also a composite measure of the frequency of the crime mapping activities and the number of different types of crimes that are mapped by the department. In other words, in order to create the intensity variable the frequency of crime mapping use was multiplied
by the types of crime mapped and in order to create the amount of information variable, the crime mapping intensity variable and crime mapping types variables were multiplied.

Figure 17 Diagram Showing Creation of Information Amount Variable

The logic behind this type of variable creation is that the more crime mapping tools are used and the more frequently they are used for mapping and geo-coding more types of crime, the more the information obtained from those activities will be. Since in each variable higher values represent higher frequency of use or higher number of tools employed or higher number of crime types mapped, when all variables are multiplied together, police departments that score higher on each of those separate measures will algebraically end up with a even higher score on the composite measure showing the amount of information that they produce.

Frequency of crime mapping use ranges from “0” to “5”, where the highest value “5” indicates daily use of crime mapping and the lowest value “0” indicates occasional use of crime mapping. The value “4” indicates weekly use of crime mapping. “3”
indicates bi-weekly use of crime mapping. “2” indicates monthly use of crime mapping. And, “1” indicates irregular use of crime mapping mostly when necessary.

The crime mapping types index was created by combining multiple survey questions that measure the phenomenon. The index is composed of the following types of crime mapping applications: (1) automated pin maps, (2) trend analyses, (3) temporal analyses, (4) offender movement, (5) pattern analyses, (6) situational analyses, (7) linkage analysis, and (8) other mapping analysis. The Cronbach’s alpha value (scale reliability coefficient) for the index is 0.7112. Although there is no certain cut-off point that is agreed upon for Cronbach’s alpha, the generally accepted minimum value is .7 (Chatterjee, Hadi, & Price, 2000). Based on this criterion the use of crime mapping index is a reliable measure of crime mapping use in police departments. In order to create the index variable all eight of the variables measuring different mapping applications were added together.

The mapped crimes index is composed of the following types of crimes that are mapped: (1) robbery, (2) homicide, (3) rape, (4) aggravated assault, (5) common assault, (6) disorderly conduct, (7) burglary, (8) larceny-theft, (9) motor vehicle, (10) theft, (11) arson, (12) weapons violations, (13) gangs, (14) drug offenses, (15) domestic violence, (16) traffic offenses, (17) forgery/fraud, (18) firearm discharges, (19) vandalism, (20) gambling, (21) kidnapping, (22) prostitution, (23) other sex offenses, and (24) driving under influence. This index is a measure of how extensively the departments map crimes.

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5 Cronbach’s alpha is a measure of internal consistency for how well multiple items or a set of variables measure a one-dimensional latent construct (R. A. Peterson, 1994). The null hypothesis tested with this statistic is that the scale is not reliable.
The Cronbach’s alpha value (scale reliability coefficient) for the index is 0.95, thus this index is a reliable measure of extensive mapping of crime types in police departments. In creating this index, the method of adding together the measures of crimes that are mapped is used.

Control variables include per capita property crime rates, per capita violent crime rates, per capita number of sworn officers, racial diversity\(^6\), and population density. Population density is a measure of population per unit area obtained by population divided by area of the jurisdiction. Descriptive statistics for the variables are presented in Table 4.

Since the dependent variable is a binary variable, binomial logistic regression will be used employing maximum likelihood estimation. The results of the analysis will be presented using Spost simulation technique. Spost provides substantial post-estimation interpretation of categorical dependent variable regression models (Long & Freese, 2006).

\[ P = \sum_{i=1}^{6} x_{i}(x_{i}-1) / P(P-1) \]

\(^6\) The formula for calculating the probability index of racial diversity is:

\[ P = \text{the total number of population}, \quad X_1 = \# \text{ White alone}, \quad X_2 = \# \text{ Black alone}, \quad X_3 = \# \text{ Native American alone}, \quad X_4 = \# \text{ Asian alone}, \quad X_5 = \# \text{ Pacific alone}, \quad X_6 = \# \text{ Other race alone}. \]
Table 4 Descriptive Statistics for the Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amount of Information Produced by the Department</td>
<td>232</td>
<td>160.86</td>
<td>219.55</td>
<td>0.00</td>
<td>1150</td>
</tr>
<tr>
<td>Violent Crime Rates</td>
<td>1713</td>
<td>0.45</td>
<td>1.41</td>
<td>0.00</td>
<td>40.57</td>
</tr>
<tr>
<td>Property Crime Rates</td>
<td>1713</td>
<td>9.81</td>
<td>11.74</td>
<td>0.00</td>
<td>115.38</td>
</tr>
<tr>
<td>Racial Diversity</td>
<td>1825</td>
<td>.25</td>
<td>.19</td>
<td>0.00</td>
<td>.81</td>
</tr>
<tr>
<td>Percent Living in Urban Areas</td>
<td>1825</td>
<td>70.16</td>
<td>38.63</td>
<td>0.00</td>
<td>100</td>
</tr>
<tr>
<td>Population Density</td>
<td>1825</td>
<td>1,765.89</td>
<td>2,525.69</td>
<td>0.39</td>
<td>30,210.16</td>
</tr>
<tr>
<td>Sworn Personnel per Capita</td>
<td>1722</td>
<td>2.48</td>
<td>4.35</td>
<td>0.00</td>
<td>123.08</td>
</tr>
</tbody>
</table>

Analysis and Results

Models

Four models were created to test the hypothesis; a linear and a non-linear model for each dependent variable.

The idea behind creating a non-linear model is that theoretically the relationship between information produced and information driven decision-making might also be presented in such a way that police departments that produce more information as a result of frequent use and employment of multiple analytical functions of crime mapping might be more likely to use the information generated by crime mapping in resource allocation decisions and redistricting decisions than departments that produce minimal information to a certain extent, when the information produced overwhelmingly increases they might be less likely to use the information for decision-making (or in other words they might be more likely to refrain from information based decision-making due to huge load of analytical information).

The logistic regression models with linear equation are formulized as in Equations 3 and 4.
\[ Y_{\text{resource allocation decisions}} = \beta_0 + \beta_1 X_{\text{amount of information}} + \beta_2 X_{\text{violent crime rates}} + \beta_3 X_{\text{property crime rates}} + \beta_4 X_{\text{racial diversity}} + \beta_5 X_{\text{percent living in urban}} + \beta_6 X_{\text{population density}} + \beta_7 X_{\text{per capita sworn personnel}} + \epsilon \]

Equation 3 Linear Regression Formula for Estimating Resource Allocation Decisions

\[ Y_{\text{redistricting decisions}} = \beta_0 + \beta_1 X_{\text{amount of information}} + \beta_2 X_{\text{violent crime rates}} + \beta_3 X_{\text{property crime rates}} + \beta_4 X_{\text{racial diversity}} + \beta_5 X_{\text{percent living in urban}} + \beta_6 X_{\text{population density}} + \beta_7 X_{\text{per capita sworn personnel}} + \epsilon \]

Equation 4 Linear Regression Formula for Estimating Redistricting Decisions

In these models the expected sign of \( \beta_1 \) is positive as hypothesized in the previous section. For each model;

- Under the null hypothesis; \( H_0; \beta_1=0 \)
- Under the alternative hypothesis; \( H_A; \beta_1>0 \)

The logistic regression models with non-linear equation are formulized as in Equations 5 and 6.

\[ Y_{\text{resource allocation decisions}} = \]
\[ \beta_0 + \beta_1 X_{\text{amount of information}} + \beta_2 X_{\text{amount of information squared}} + \beta_3 X_{\text{violent crime rates}} + \beta_4 X_{\text{property crime rates}} + \beta_5 X_{\text{racial diversity}} + \beta_6 X_{\text{percent living in urban}} + \beta_7 X_{\text{population density}} + \beta_8 X_{\text{per capita sworn personnel}} + \epsilon \]

Equation 5 Non-Linear Regression Formula for Estimating Resource Allocation Decisions

\[ Y_{\text{redistricting decisions}} = \]
\[ \beta_0 + \beta_1 X_{\text{amount of information}} + \beta_2 X_{\text{amount of information squared}} + \beta_3 X_{\text{violent crime rates}} + \beta_4 X_{\text{property crime rates}} + \beta_5 X_{\text{racial diversity}} + \beta_6 X_{\text{percent living in urban}} + \beta_7 X_{\text{population density}} + \beta_8 X_{\text{per capita sworn personnel}} + \epsilon \]

Equation 6 Non-Linear Regression Formula for Estimating Redistricting Decisions

In the non-linear models, the expected sign of \( \beta_1 \) is positive and the expected sign of \( \beta_2 \) is negative since as explained above, to a certain extent, as the amount of information police departments produce increase, the likelihood of using the information
in resource allocation decisions and redistricting decisions also increase, but after a point the likelihood of using the information for decision-making decreases. For each model:

- Under the null hypothesis; $H_0; \beta_1=0$ and $\beta_2=0$
- Under the alternative hypothesis; $H_A; \beta_1>0$ and $\beta_2<0$

Since the hypothesized relationships are one tailed the results of the regression analyses below will be interpreted accordingly.

**Analysis**

For maximum likelihood estimation, Stata statistical package was used. As part of logistic regression diagnostics, perfect collinearity among the independent variables was checked for both models. Models were examined by looking at the R-squared values of regression models in which each independent variable in our original model was entered as a dependent variable and regressed on the remaining independent variables\(^7\).

According to collinearity statistics multi-collinearity was not detected in our model since the largest variance inflation factor (VIF) is not greater than 10 (Belsley, Kuh, & Welsch, 1980; Greene, 2003).

For outliers and influential cases the diagnostics suggested by Long and Freese (2006) were followed. Residuals were examined in order to check for outliers but none were found. The models were examined for influential leverage of the cases but no

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\(^7\) For multi-collinearity diagnostic, the “collin” command in Stata was used. This command was developed by UCLA ATS Statistical Consulting Group for data analysis for computing several collinearity diagnostic measures including VIF, tolerance, eigenvalues, condition index, and R-squared in Stata.
influential cases were found that would affect the models. The results of the logistic regression modeling are given in Table 5.

The linear model for predicting the probability of police departments using the information obtained from crime mapping in resource allocation decision is statistically significant (chi-square value=18.04, p<.01). The pseudo $R^2$ shows that only 6.6% of the variation in the dependent variable is explained by the included independent variables in this model. None of the control variables significantly predicts the use of information for resource allocation decisions. As hypothesized, the explanatory variable measuring the amount of information produced by the police departments is a highly significant predictor of the dependent variable (p<.01).

This suggests that police departments that produce more information are more likely to use the information in decision-making. In other words, agencies that engage in more crime mapping activities, by mapping more types of crimes, by doing more frequent mapping and by using more crime mapping tools, are more likely to base their resource allocation decisions on the information provided by those activities. In that sense, we reject the null hypothesis that there is no difference in using the information generated by crime mapping in resource allocation decisions between police departments that produce huge amounts of information (as a result of frequent use and employment of multiple analytical functions of crime mapping) and departments that produce relatively less amounts of information.

---

8 For outliers standardized residuals were examined on a scatter plot. For influential cases Cook’s distance values were examined.
The testing of the second hypothesis requires use of a non-linear relationship and thus it should be stated as a polynomial function (in this case a quadratic polynomial). On a scatter plot the expected look is an initial upward trend in likelihood of using information for decision-making and after a certain point a downward trend showing a decline in likelihood of using information for decision-making. In order to capture this theoretical downward trend the explanatory variable amount of information was squared and this squared term was added into the regression model as an explanatory variable.

The quadratic model for predicting the probability of police departments using the information obtained from crime mapping in resource allocation decision is statistically significant (chi-square value=25.35, p<.001). The pseudo R² shows that 9.3% of the variation in the dependent variable is explained by the included independent variables in this model. In this model also, none of the control variables significantly predicts the use of information for resource allocation decisions. Nevertheless, the non-linear model is a clear improvement on the linear model since the chi-squared and the pseudo R² values increased. Moreover, both explanatory variables measuring the amount of information produced by the police departments are statistically significant as hypothesized (p<.01 and p<.001 respectively).

This suggests that police departments that produce information from crime mapping activities are likely to use the information in resource allocation decisions to some extent, when the amount of information increases the likelihood decreases. The squared amount of information variable captures this trend. The signs of the coefficients clearly show this relationship since the positive coefficient on the amount of information
variable suggests an increasing relationship and the negative sign on the squared amount of information variable suggests a decreasing relationship. In other words, agencies that engage in more crime mapping activities, by mapping more types of crimes, by doing more frequent mapping and by using more crime mapping tools, are likely to refrain from basing their resource allocation decisions on the information provided by those activities. In that sense, we reject the second null hypothesis.
Table 5 The Impact of Information on Resource Allocation Decisions

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model - 1 Linear Model</th>
<th>Model - 2 Quadratic Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amount of Information</td>
<td>.003** ( (0.001) )</td>
<td>.009*** ( (0.002) )</td>
</tr>
<tr>
<td>Amount of Information Squared</td>
<td>(-8.41e-06** ( (3.09e-06) )</td>
<td></td>
</tr>
</tbody>
</table>

**Control Variables**

<table>
<thead>
<tr>
<th></th>
<th>Model - 1 Linear Model</th>
<th>Model - 2 Quadratic Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Violent Crime Rates</td>
<td>.002 ( (0.002) )</td>
<td>.002 ( (0.002) )</td>
</tr>
<tr>
<td>Property Crime Rates</td>
<td>-2.05e-06 ( (0.001) )</td>
<td>-.0001 ( (0.001) )</td>
</tr>
<tr>
<td>Racial Diversity</td>
<td>.894 ( (1.215) )</td>
<td>.799 ( (1.236) )</td>
</tr>
<tr>
<td>Percent Living in Urban Areas</td>
<td>.0113 ( (0.019) )</td>
<td>.011 ( (0.019) )</td>
</tr>
<tr>
<td>Population Density</td>
<td>.0001 ( (0.001) )</td>
<td>.0001 ( (0.001) )</td>
</tr>
<tr>
<td>Sworn Personnel per Capita</td>
<td>-.160 ( (0.193) )</td>
<td>-.158 ( (0.207) )</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.526 ( (1.683) )</td>
<td>-1.649 ( (1.728) )</td>
</tr>
</tbody>
</table>

Log Likelihood: -126.49377 \( \text{Model - 1} \)  \(-122.83929 \( \text{Model - 2} \)

Chi-square: 18.04** \( \text{Model - 1} \)  \(25.35*** \( \text{Model - 2} \)

Pseudo R\(^2\): .066 \( \text{Model - 1} \)  \(.093 \( \text{Model - 2} \)

Number of Cases: 199 \( \text{Model - 1} \)  \(199 \( \text{Model - 2} \)

Notes: Coefficients are logistic regression coefficients with standard errors reported in parenthesis. Significance levels based on a one-tailed test: ***, ***, ***, ***, *. Pseudo R\(^2\) (McFadden R\(^2\)) is a measure of fit that is similar to the R\(^2\) in OLS regression.
The linear model for predicting the probability of police departments using the information obtained from crime mapping in *redistricting decision* is statistically significant (chi-square value=23.22, p<.01). The pseudo R² shows that 9.2% of the variation in the dependent variable is explained by this model. The control variables do not significantly predict the use of information for redistricting decisions however, the amount of information produced by the police departments is, as hypothesized, a highly significant predictor of the dependent variable (p<.001). This suggests that police departments that produce more information are more likely to use the information in redistricting decisions. In that sense, we reject the null hypothesis that there is no difference in using the information generated by crime mapping in redistricting decisions between police departments that produce huge amounts of information (as a result of frequent use and employment of multiple analytical functions of crime mapping) and departments that produce relatively less amounts of information.

As with the previous model, the testing of the second hypothesis requires use of a quadratic relationship and thus the squared amount of information variable was added into this regression model as an explanatory variable as well.

The quadratic model for predicting the probability of police departments using the information obtained from crime mapping in resource allocation decision is statistically significant (chi-square value=26.38, p<.001). The pseudo R² shows that 10% of the variation in the dependent variable is explained by the included independent variables in this model. In this model also, none of the control variables significantly predicts the use of information for redistricting decisions. Nevertheless, the non-linear model is an
improvement on the linear model since the chi-squared and the Pseudo R² values increased. Although the squared amount of information variable is not statistically significant at .05 alpha level for a two-tailed hypothesis test, it is considered statistically significant in this study at .05 alpha level ($p = \frac{.062}{2} = .031$) for a one-tailed hypothesis test with the expected negative sign of the coefficient.

This suggests that police departments that produce information from crime mapping activities are likely to use the information in redistricting decisions to some extent, when the amount of information increases the likelihood decreases. With both variables being statistically significant and with the expected direction of the relationship, we can conclude that agencies that engage in more crime mapping activities, by mapping more types of crimes, by doing more frequent mapping and by using more crime mapping tools, are likely to refrain from basing their redistricting decisions on the information provided by those activities.
### Table 6 The Impact of Information on Redistricting Decisions

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model - 1 Linear Model</th>
<th>Model - 2 Quadratic Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amount of Information</td>
<td>.003***</td>
<td>.008***</td>
</tr>
<tr>
<td></td>
<td>(.0001)</td>
<td>(.002)</td>
</tr>
<tr>
<td>Amount of Information Squared</td>
<td>-5.52e-06*</td>
<td>(2.96e-06)</td>
</tr>
</tbody>
</table>

**Control Variables**

<table>
<thead>
<tr>
<th></th>
<th>Model - 1 Linear Model</th>
<th>Model - 2 Quadratic Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Violent Crime Rates</td>
<td>.002</td>
<td>.002</td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td>(.002)</td>
</tr>
<tr>
<td>Property Crime Rates</td>
<td>-.0001</td>
<td>-.0001</td>
</tr>
<tr>
<td></td>
<td>(.001)</td>
<td>(.001)</td>
</tr>
<tr>
<td>Racial Diversity</td>
<td>.216</td>
<td>.287</td>
</tr>
<tr>
<td></td>
<td>(1.328)</td>
<td>(1.336)</td>
</tr>
<tr>
<td>Percent Living in Urban Areas</td>
<td>.008</td>
<td>.007</td>
</tr>
<tr>
<td></td>
<td>(.02)</td>
<td>(.021)</td>
</tr>
<tr>
<td>Population Density</td>
<td>.0001</td>
<td>.0001</td>
</tr>
<tr>
<td></td>
<td>(.001)</td>
<td>(.001)</td>
</tr>
<tr>
<td>Sworn Personnel per Capita</td>
<td>-.021</td>
<td>-.012</td>
</tr>
<tr>
<td></td>
<td>(.179)</td>
<td>(.185)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.822</td>
<td>-1.891</td>
</tr>
<tr>
<td></td>
<td>(1.893)</td>
<td>(1.931)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-114.11441</td>
<td>-112.53136</td>
</tr>
<tr>
<td>Chi-square</td>
<td>23.22**</td>
<td>26.38***</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.092</td>
<td>.1</td>
</tr>
<tr>
<td>Number of Cases</td>
<td>199</td>
<td>199</td>
</tr>
</tbody>
</table>

Notes: Coefficients are logistic regression coefficients with standard errors reported in parenthesis. Significance levels based on a one-tailed test: ***<.001, **<.01, *<.05. Pseudo R² (McFadden R²) is a measure of fit that is similar to the R² in OLS regression.
Since in logistic regression, unlike OLS, we predict probabilities instead of predicting actual values, the substantial interpretation of the coefficients obtained in the analysis can be enhanced by computing the predicted probabilities for various values of the independent variables using a simulation technique. For this purpose, the SPost post-estimation software (Long & Freese, 2006) was used for interpretation of the results of analysis in the models. The logit coefficients show the effect of a unit change in each independent variable on the cumulative normal distribution of the probability of using information for resource allocation or redistricting decisions.

Since the cumulative normal is an S-shaped curve and not linear, the size of the effect is different at different points of the curve. Location on the curve depends on the values of all the variables included in the model. Certain values can be assigned to the independent variables and by changing the value of the independent variable that is of most interest while holding all independent variables constant, the change in predicted probabilities associated with varying values of the independent variables can be calculated. SPost post estimation software also provides the standard errors for each predicted probability.

For each model, three different representative characteristics of the cases were constructed by changing the values for the amount of information variable from minimum to maximum.

Table 7 presents the change in predicted probabilities across different values of mapped crimes index for agencies that do neither hot spots analysis nor trend analysis and agencies that do both.
## Table 7 Predicted Probabilities of Using Information for Decision-Making

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Predicted Probability</th>
<th>Difference (min to mean)</th>
<th>Difference (mean to max)</th>
<th>Difference (min to max)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mapped Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Index=1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot Spots=0</td>
<td>0.1768</td>
<td>0.1248</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mapped Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.3016</td>
<td>0.2452</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot Spots=0</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mapped Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Index=23</td>
<td>0.5468</td>
<td></td>
<td>0.37</td>
<td></td>
</tr>
<tr>
<td>Hot Spots=0</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mapped Crimes</td>
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<td></td>
</tr>
<tr>
<td>Index=1</td>
<td>0.5448</td>
<td>0.1616</td>
<td></td>
<td></td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=1</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Mapped Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Index=11</td>
<td>0.7064</td>
<td>0.1641</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot Spots=1</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=1</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mapped Crimes</td>
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<td></td>
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<tr>
<td>Index=23</td>
<td>0.8705</td>
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<td>0.3257</td>
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</tr>
<tr>
<td>Hot Spots=1</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
For an agency not using hot spots analysis and trend analysis, the probability of using information obtained from crime mapping for decision-making is 17% when the minimum numbers of crimes were mapped in the department. This probability increased by 13% to 30% when the department maps more crimes. When the maximum numbers of crimes were mapped the probability is 54% which is a 24% increase from average use of crime mapping and a 37% increase from the minimum use of crime mapping.

For an agency that employs both hot spots analysis and trend analysis, the probability of using information obtained from crime mapping for decision-making is 55% when the minimum numbers of crimes were mapped in the department. This probability increased by 15% up to 70% when the department mapped average number of various crime types. When the maximum numbers of crimes were mapped, the probability is 87% which is a 16% increase from average use of crime mapping and a 32% increase from minimum use of crime mapping.
The slope change point in Figure 18 is $512.95482$. The value of the point at which the slope changes can be calculated using the formula in Equation 7 (W. D. Berry & Feldman, 1985, p. 59).

$$X_{at \ tip\ point} = \frac{-\beta_1}{2 \beta_2}$$

**Equation 7 Slope Change Point formula**

The increase in the probability of using information obtained from crime mapping for decision-making when hot spots analysis and trend analysis are used and when more crime types are mapped can be seen visually from the graph in Figure 18.
Table 8 presents the change in predicted probabilities of using information for redistricting across different values of mapped crimes index for agencies that do neither hot spots analysis nor trend analysis and agencies that do both.

For an agency not using hot spots analysis and trend analysis, the probability of using information obtained from crime mapping for redistricting decisions is 10% when the minimum numbers of crimes were mapped in the department. This probability increased by 10% up to 20% when the department maps more crimes. When maximum the numbers of crimes were mapped the probability is 45% which is a 25% increase from average use of crime mapping and a 35% increase from minimum use of crime mapping.

For an agency that employs both hot spots analysis and trend analysis, the probability of using information obtained from crime mapping for decision-making is 20% when the minimum numbers of crimes were mapped in the department. This probability increased by 16% up to 36% when the department maps average number of various crime types. When maximum number of crimes is mapped the probability is 65% which is a 29% increase from average use of crime mapping and a 45% increase from minimum use of crime mapping.
<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Predicted Probability</th>
<th>Difference (min to mean)</th>
<th>Difference (mean to max)</th>
<th>Difference (min to max)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mapped Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Index=1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot Spots=0</td>
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<td></td>
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<tr>
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<td></td>
<td></td>
</tr>
<tr>
<td>Mapped Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Index=11</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot Spots=0</td>
<td>0.2029</td>
<td>0.2503</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mapped Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Index=23</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot Spots=0</td>
<td>0.4532</td>
<td>0.3508</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mapped Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Index=1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot Spots=1</td>
<td>0.2082</td>
<td>0.1615</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=1</td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Mapped Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Index=11</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot Spots=1</td>
<td>0.3697</td>
<td>0.2867</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend Analysis=1</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Mapped Crimes</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Index=23</td>
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</tr>
<tr>
<td>Hot Spots=1</td>
<td>0.6564</td>
<td>0.4482</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The slope change point in Figure 19 is 689.90942. The increase in probability of using information obtained from crime mapping for redistricting decisions when more crime types are mapped can visually be seen on the graph in Figure 19.

The analyses and the illustrations suggest that mapping more crime types in a department increases the probability of using information provided by crime mapping for resource allocation and redistricting decisions regardless of whether hot spots analysis or trend analysis are employed in the department. It should be noted, however, that when hot spots analysis and trend analysis are used, the probability of using information for resource allocation decisions increases. In this regard, more mapping functions create
incentives for using the analytical information obtained from such functions in decision-making.

**Conclusion**

In this chapter the main research objective was to examine whether the information obtained from crime mapping has an impact on managerial decision-making in police departments. In particular, the statistical analysis conducted focused on whether the probability of making decisions about redistricting the jurisdiction and resource allocation increase as the amount of information obtained from crime mapping increase. The results suggest that to a certain extent police departments are likely to use information obtained from crime mapping in resource allocation and redistricting decisions. When the amount of information reaches a certain point, which indicates that the information produced is beyond examination and evaluation for decision-making, the departments are less likely to base such critical decisions on information acquired from crime mapping.
CHAPTER 5

CRIME MAPPING AND CRIME ANALYSIS

Introduction

In this chapter, I test the proposition that the use of crime analysis and crime mapping are effective tools in crime reduction and crime solving. By enabling the police to proactively react to problematic areas, crime analysis and crime mapping potentially create a deterrent effect by increasing the likelihood of arrest. The chapter starts with a succinct discussion of how crime analysis and crime mapping technologies became indispensable tools for law enforcement in their ongoing fight against crime. Yet despite a large literature extolling the virtues of crime mapping, very little systematic research investigates whether this tool is effective in reducing crime rates and increasing crime clearances. Having reviewed the theoretical arguments for expecting a crime mapping effect, I outline the testable implications, describe an empirical test of those implications, interpret the results and conclude by considering the implications of my findings.

Crime Analysis and Crime Mapping

Historically, traditional police work has mainly been either passive, such as random patrolling, or reactionary such as responding to calls. With the widespread introduction of advanced information technology into policing and with the continued use
of analysis methods, the police have begun to be more proactive and be able to understand the extent and nature of crime. Technological advances enabled police to predict and identify problematic areas and create specific approaches to solve those problems.

Like all organizations, police departments must adapt to survive and adjust their administrative and operational arrangements to accommodate rapid changes in technological, social, economic, and political conditions (O'Shea & Nicholls, 2003). It is argued that most of the significant changes in city police in America in the last century resulted from technology (Haller, 1996). Among those advances probably the singular most important are increased computer storage capacity and analytical retrieval of stored information. Initially, computerized applications as we use today were limited since the software used was not particularly user-friendly and highly complicated. Also few law enforcement agencies had computers in the 1970s and fewer had personnel capable and educated enough to operate computers and run analytical queries (M. B. Peterson, 1994).

Enhanced effectiveness and efficiency in both operational and administrative functions of the institutions are universally accepted as the basic rationale for introducing technical and technological change within any organization, the police being no exception. Since the early 1970s, the concept of computerized policing has been continuously evolving in line with technological advances in other fields and the changing nature and the concept of policing (Hoey, 1998).

Since the use of information technology has become prevalent throughout society, its application to crime and justice is a necessity (Tolbert, Mossberger, & Stansbury,
The 1990s heralded a fresh era in computerized policing, since it has been claimed that the new technology must be useful because it has been widely utilized by many other types of organizations (Ackroyd, 1992). With the notion that what worked for others should also work for the police, police organizations across the U.S. started to adopt new technologies and invest vast amounts of money in computerized policing.

The argument for technology within the police services is that computerization can lead to enhanced efficiency, competency and professionalism. Information technology and computerized data analysis are being recognized as valuable tools in management, command and control, and crime analysis, which is the way forward for policing in general (Hoey, 1998).

Information technology has been used within the police services to gather and manage all sorts of information (management), to facilitate the efficient deployment of labor, reallocation of resources, and redistricting activities, to enable quick responses (command and control) (Hoey, 1998), and to develop strategies, whether it is for a small-scale operation or the management of the police force nationally (computer applications relating to crime analysis).

Crime analysis, according to some, is considered to be “one of the most powerful tools with capacity, if applied ‘on the ground,’ to prevent, reduce and control crime and disorder” (Manning, 2001, p. 83). In this context, the number of police departments using computerized records management systems to store, analyze and retrieve data has increased in recent years. Because of this, police managers now understand better the need for data and information and how computers can serve their needs (Worrall, et al.,
Crime analysis refers to the use of data routinely collected by an agency to support police operations through strategic planning, manpower deployment and investigative assistance. Crime analysis techniques can be traced as far back as 1896, to a system originally developed by Scotland Yard for classifying criminals by their modus operandi. Since then, crime analysis has expanded to include the following types: crime pattern detection, crime-suspect correlation, target profile analysis, forecasting crime potential, exception reports, forecasting crime trends and resource allocation (Greenfeld, 1994).

Police crime analysis operations consist of three essential functions: (1) to assess the nature, extent, and distribution of crime in order to efficiently and effectively allocate resources and deploy personnel to needed areas, (2) to identify crime–suspect correlations to assist investigations, and (3) to identify the specific conditions that facilitate crime and incivility so that policymakers may make informed decisions about prevention approaches (Reuland, 1997).

Crime analysis is not simply a supportive function; it brings together criminology, criminal justice, criminal investigation and crime prevention along with different areas from different fields such as geography, in order to come up with real solutions to the crime phenomenon. The growth and extension of crime analysis as a strategic and administrative tool is associated with the development of recent policing approaches such as community-oriented policing and problem-oriented policing for which intelligence is used in order to target police activity (Cope, 2004). Strategic and administrative crime
analysis is mainly concerned with planning for long term goals, examining crime trends and providing support to administrators as they determine and allocate resources (Osborne & Wernicke, 2003).

The two purposes of crime analysis – to prevent crime and to arrest offenders (M. B. Peterson, 1994) – make it a highly efficient tool and separate it from investigative analysis in the sense that crime analysis not only supports solving crimes and prosecuting criminals but it also supports deterring crime through preventive patrol or other proactive activities. Crime analysis is described as an effective service for patrol officers and detectives in locating and bringing the criminal offenders before justice. The interest in crime analysis by police departments has been increasing since it is considered as a critical and vital function with regards to its capacity to be cost-effective and affect crime and clearance rates (Haley, Todd, & Stallo, 1998).

According to Osborne and Wernicke, (2003) there are five basic steps in crime analysis: collection, collation, analysis, dissemination and feedback. Collection refers to the gathering of necessary data by the crime analyst from available sources like crime incident reports, investigative follow-up records, calls-for-service records and arrest records. Collation involves classification, categorization and organization of collected information and making it ready for the next step, analysis. The analysis stage is the core of the entire crime analysis process since at this stage the raw data is turned into timely, useful, accurate and actionable information on crime series, patterns and trends and prepared for dissemination. The dissemination step simply refers to distribution of analyzed data to relevant levels of the department to be operationalized. With feedback
from the field personnel the analysis process is adjusted based on the needs of the officers or the requirements of specific situations.

An essential tool for crime analysis is crime mapping. Crime has been mapped virtually by police officers or civilian staff for over a century. However, such mapping practices have been achieved through the use of pushpins and a paper map until the introduction of Geographic Information Systems (GIS). The introduction and use of GIS in police work has been a slow process due to the costs of software and hardware for GIS but today GIS is utilized in many police departments for crime analysis (La Vigne & Groff, 2001b). GIS allows police departments to map crime areas, determine hot spots, identify trends and thus enable the decision makers to take further measures. By providing means to the police departments to determine relationships between certain crimes and crime locations, use of GIS proved to be effective in fighting certain crimes especially property crimes such as theft and burglary (Woodby, 2003). Once a crime prevention program has been implemented, GIS can also help departments identify crime displacements by visually detecting changing crime concentrations and inform further crime prevention activities.

From the very first stage of data collection through the monitoring and evaluation of any targeted activity, crime mapping has a vital role in the policing and crime reduction process. However, crime mapping can also serve as a crucial and key mechanism at a more fundamental stage; the stage before the crime occurs by helping in the planning of initiatives that are successful in handling a crime problem (Chainey & Ratcliffe, 2005, p. 4).
The use of mapping methods such as GIS, has been a part of policing for the last thirty years, however most applications were based on examining the criminal phenomena and linked factors that already occurred, which is a reactionary approach to crime. These retrospective mapping efforts have been effective and useful but the promise of crime mapping lies in its capacity to identify early warning signs across time and space, and make a proactive approach in making problem solving and crime prevention possible (La Vigne & Groff, 2001b). In that sense “the real power of a GIS lies not in the printed output, but in the ability to interact with the data” (Chainey & Ratcliffe, 2005, p. 8) and provide analytical information. Therefore, crime analysis not only assists police departments to react swiftly and on time when a crime occurs but they also provide adequate information to predict future crimes.

“Crime mapping has the following application areas; (1) Recording and mapping police activity, crime reduction projects, calls for service and crime incidents, (2) Supporting the briefing of operational police officers by identifying crimes that have recently occurred and predicting where crime may occur in the future, (3) Identifying crime hotspots for targeting, deploying and allocating suitable crime reduction responses, (5) Helping to effectively understand crime distribution, and to explore the mechanisms, dynamics and generators to criminal activity, through pattern analysis with other local data, (6) Monitoring the impact of crime reduction initiatives, and (7) Using maps as a medium to communicate to the public the crime statistics for their area and the initiatives that are being implemented to tackle crime problems” (Chainey & Ratcliffe, 2005, p. 4).

Crime analysis and especially crime mapping, when effectively conducted and evaluated, can be assets to the police department in its various activities and to the police manager in decision-making as shown in the decision-making chapter. Current use, however, of crime analysis and crime mapping in police departments across the U.S. is not yet strategic. Police can produce volumes and computer loads of intelligence and information, which only becomes useful operationally after being interpreted, evaluated,
assessed and any potential patterns and linkages investigated. Since “it is in the
translation of raw information into operationally viable intelligence, that analysis plays its
crucial role” and becomes a real asset to the police department where it is used in this
context (Cope, 2004, p. 201).

As we move into the new century successful applications and case studies of GIS
in law enforcement agencies across the U.S. clearly illustrate that crime mapping
technologies, with their broad range of potential applications, are playing an increasingly
vital role in fighting crime (Leipnik & Albert, 2003a, p. 111).

Casady (2003) shows that Lincoln Police Department in Nebraska has
successfully operated GIS in crime reduction and management of resources. In
Knoxville, Tennessee the police have managed to improve the efficiency of the
community-oriented policing strategy by employing GIS and crime analysis using GIS
(Hubbs, 2003). The Phoenix Police Department in Arizona has successfully applied GIS
in order to investigate serial robberies and created best practice for serial crimes (Hill,
2003). Boston Police Department has applied complex and robust analytical components
of GIS to support their neighborhood policing activities (Walter, 2003). In another
success story from Spokane, Washington, the police have applied geo-spatial
technologies to homicide investigations and have managed apprehension of perpetrators
(Leipnik, et al., 2003).

 Despite many success stories, the impact of crime analysis and crime mapping on
crime prevention and crime reduction at the national level is yet to be tested. There are
only limited studies on the use of crime analysis and crime mapping by the police and
few have attempted to measure the impact of those technologies on police effectiveness. If the effectiveness of using crime analysis and crime mapping as powerful analytic tools in crime prevention and crime reduction can be presented, further studies to find better ways to get the most out of crime analysis and crime mapping can be done. Also investment in police technology can become more cost effective.

In the literature there are studies concerning the impact of using technology on police work. Such as studies on the impact of mobile computing on police performance (Ioimo & Aronson, 2004), use of military technology by police for intelligence gathering (Nunn, 2001), administrative, technological, and operational functions of the police crime analysis (O'Shea & Nicholls, 2003), crime mapping and training needs of police personnel (Ratcliffe, 2004), and impact of mobile data terminals on patrol officer’s work (Meehan, 1998). However, most of these studies focus on the field officer’s productivity, difference that technology makes in performing daily tasks etc. There is a gap in the literature about the impact of technology use on police overall effectiveness in terms of decreasing crime rates and increasing clearances.

**Theory and Hypotheses**

Criminal justice theories and practitioners generally focus on the social and individual manifestations of the phenomenon of crime and rarely study the temporal or spatial appearances of crime. However, the spatial and temporal aspects of crime have as many implications in terms of crime prevention as the individual aspects do. Focusing on individual criminality highly limits the crime prevention efforts of the police. First of all
this requires detection of potential criminals so that they can be targeted with psychological or social programs. Or individual level efforts might include rehabilitation programs which means that the crime has already occurred and now the focus is on preventing repeat offending.

In both cases the police have a small role to play. Detecting potential criminals requires sociological, psychological and even anthropological expertise and generally targets early stages of adolescence. In rehabilitation or in restorative justice, on the other hand, once out of the police’s hands, the case is either transferred to corrections or restorative justice institutions, where police have little or no say.

In that sense, police effectiveness in terms of decreased crime rates and increased crime clearances has long been a subject of debate among practitioners of the criminal justice field as the police seem to be making the arrest mostly because of the naiveté of the criminal and merely completing the paperwork before sending the suspect before the court. Although the public would have the opinion that the more police recruited, the less crime committed, empirical studies on the issue suggest that the size of the police force has little effect on crime prevention when compared to social institutions like family (Sherman, 2002).

In fact, Bayley (1994) in his most cited book claims that the impact of police on crime is a myth. In addition, he argues, based on repeated analyses that have consistently failed to find any connection between the number of police officers and crime rates, that the police do not prevent crime. Some scholars, however, argue that use of certain police strategies under certain conditions such as directed patrol, proactive arrests and problem-
solving at crime hot spots have potential to effectively prevent crime (Sherman, 1997). The presence of police at the right place at the right time would have positive effects in crime prevention (Sherman, Gartin, & Buerger, 1989).

Particularly the Kansas City study showed that it was not how many officers an agency had but what the agency did with those officers is what matters (Kelling, 1974). It is suggested in the study that as opposed to the random patrol approach, the most effective use of the patrol force was achieved when officers were placed in the right areas at the right times both in terms of preventing crimes and solving crimes. Sherman and Weisburd (1995) also concluded in their study on patrol in crime hot spots that increase in police patrol presence within high crime locations can cause reductions in crime and particularly in disorderly conduct. It is argued in the study that if urban police agencies give more priority to hot spot patrols, the amount of the crime reduction will be even greater. The key to success, in that sense, in terms of effective policing by being present at the right places at the right times is the use of powerful and rich analysis tools.

It is argued by Cohen and Felson (2003) that in order for a crime to occur, motivated offenders must converge with suitable targets in the absence of capable guardians, who, in a general sense, are the police. Ekblom and Tilley (2000) suggest that a criminal event happens with the right conjunction of criminal opportunity. This involves mainly the combination of these factors: (1) a vulnerable and attractive target of crime in a vulnerable target enclosure; (2) the absence of willing and able crime preventers; (3) a potential offender who is criminally predisposed, motivated and adequately resourced for crime.
It is not easy to avoid situations where these factors come together. It is not always easy to determine who will become a vulnerable target and warn them, or control for the other factors. However, the presence of willing and able crime preventers - for the purpose of this research, the police - can be achieved by carefully examining the criminal incidents and the situations in which they occur.

We know that we cannot reserve a police officer for all potential criminals. A spatial or temporal focus on crime, as opposed to other strategies, helps police better in terms of crime prevention since such a focus shrinks the targeted area for the police. A discussion of criminal motivation and how to stop criminals from offending is beyond the scope and purpose of this study. It would be nothing but utopia to expect from crime analysis and crime mapping something that conventional criminologists have not been able to achieve in hundreds of thousands of pages and numerous studies for over more than a century (Vellani & Nahoun, 2001).

Along with or maybe even as opposed to targeting individuals prone to crime, which requires lots of labor and funding, on a more strategic level, now the police can focus on a certain area or a certain season of the year for preventing crime. Also on a more specific level, based on a case by case analysis, the police can focus on certain aspects of the criminal incident (places, individuals, connections etc.) and solve individual crimes.

A practical approach along the same theoretical lines is situational crime prevention. Informed primarily by routine activity (Cohen & Felson, 2003), rational choice (Cornish & Clarke, 1986) and other opportunity theories, situational crime
prevention is an effort to reduce opportunities for certain crimes by increasing the associated risks and difficulties and reducing the rewards of the criminal activity (Clarke, 1995). Crime analysis and crime mapping help identify the vulnerabilities of potential targets of criminal activities and can offer opportunity-reducing techniques that range from simple target hardening methods to more sophisticated means of deflecting offenders and reducing inducements (Chainey & Ratcliffe, 2005, p. 93; Clarke, 1995, p. 91).

Based on the literature outlined above, this study asserts that use of crime analysis and crime mapping by police departments increases their capacity to detect and solve crimes. The theoretical argument behind this assertion is that by detecting the hot spots of crime and increasing the ability of the police to be present at needy locations as opposed to random presence, crime analysis and crime mapping use decreases the absence of the police as capable guardians (Cohen & Felson, 2003).

Moreover, by enabling the police to detect criminal patterns over time and across space, resources of the police can be reallocated better and crime prevention activities can be reconsidered and reshaped accordingly. Although there is no theoretical claim in the literature about the crime solving capabilities of the police, this study asserts that crime analysis and crime mapping help police solve crime by enabling the investigators to establish links with evidence to the criminal thus increase crime clearances.

In essence, arresting offenders is one of the two major benefits of crime analysis and crime mapping (M. B. Peterson, 1994), by enabling the police to identify crime-suspect correlations in investigations (Reuland, 1997), and relating offence locations to
those of previous offenders and known suspects (Hirschfield, 2001). Through use of crime analysis and crime mapping, crimes have a better chance of being solved since by giving officers and supervisors the ability to pose their own queries concerning specific investigations, information is disseminated faster and intelligence can be generated through more readily available information (Astler, 2002).

Therefore, the main research question in this part of the study is whether crime analysis and crime mapping use has any effect on increasing crime clearances. The hypothesis derived from this question is stated below;

Police departments that adopt crime analysis and crime mapping have higher total number of crime clearances, violent crime clearances and property crime clearances than departments that do not adopt crime analysis and crime mapping.

Methodology

One common problem in predicting crime clearances as dependent variables with police related independent variables such as the number of police, the type of policing strategy used or the type of police technology employed is endogeneity (simultaneity). Although often used in the field of economics, modeling behavior as simultaneous equations systems is rare in the criminal justice field. In simultaneous equations systems the main independent variable and the dependent variable in the model are endogenously determined by each other and some additional exogenous variables (Baum, 2006; Wooldridge, 2002).

In such models there is a feedback effect between the endogenous independent
variable and the endogenous dependent variable. While crime analysis and crime mapping use might have an impact on crime clearances, crime analysis and crime mapping use might also be a response of the police department to decreased crime clearance rates. The theoretical background of the relationship between police and crime is that as the number of police increases there is going to be less crime (Wilson & Boland, 1978). However increasing the number of police can merely be a reaction to increased crime rates or decreased crime clearances. In fact Gerber (1996) argues that when crime is the most pressing issue in the eyes of the public, legislators are more likely to respond with appropriate legislation and policy innovations and this usually, if not always, manifests itself as an increase in the number of police.

When addressing the problem of endogeneity, initially, a test of endogeneity (such as a Hausman-type or Wald test) might be employed in order to test whether there is a feedback effect (Durbin, 1954; Hausman, 1978; Wu, 1973). Meanwhile, the problem of endogeneity can also be considered as given due to the theoretical nature of the relationship between the main explanatory variables and the dependent variables. Treating a variable as exogenous, when it really should be endogenous because there is some feedback, will result in biased and inconsistent parameter estimates.

According to Alvarez and Glasgow (1999) in cases where the researcher suspects endogeneity for theoretical reasons, the relationships should be modeled accordingly since ignoring endogeneity leads to biased estimates. It should not, however, be disregarded that in cases where there is no endogeneity and the model is treated as such, there is an important cost to it; that is the variance of the instrument variable estimator is
always larger than the variance of the ordinary least squares regression estimator (Wooldridge, 2002, p. 467).

In that sense, if there is a feedback effect as a result of the exogeneity test, in order to test the hypotheses concerning the impact of crime analysis and crime mapping use on police effectiveness, I will use two stages least squares (2SLS) or another appropriate method that corrects for the endogeneity problem. Otherwise, I will construct the models as exogenous.

In order to test the afore-mentioned hypothesis, I employ two different approaches due to the \textit{theoretically endogenous} nature of the relationship between police effectiveness measures and information technologies measures. Endogeneity is a hard to tackle problem in quantitative research and generally requires multiple methods to be used for the results to be robust and reliable. Therefore, in this research I will use both cross-sectional analysis using instrument variable estimation and static score/conditional change panel data analysis.

Moreover, since theoretically and practically, crime mapping and crime analysis increase police effectiveness, the research hypotheses are directional and all analyses are based on a one-tailed test.

\textit{Cross-Sectional Analysis}

In the CCMLE survey, the departments that do and do not use crime mapping are asked separate questions and there are limited questions common to both groups. Also very limited questions are asked concerning department level factors that would affect
policing outputs. For that reason, as explained in Chapter 2, CCMLE data was merged with LEMAS data in order to add organizational factors in the analysis. Although there already are measures of crime mapping and crime analysis in LEMAS data at the department level, the strength of CCMLE data, thus the merged data, is that the measures of crime mapping and crime analysis in CCMLE data are more detailed, less ambiguous and most importantly they are more reliable and valid.

Variables

The dependent variable in this part is number of crime clearances per 1,000 population for total crime clearances, violent crime clearances and property crime clearances. Crime clearances as measured in UCR are actual number of clearances by arrest; crimes that are cleared without intervention or investigation of police are not included in the data set. Furthermore, clearance rates measured by number clearances per number of crimes is deliberately not used to measure police effectiveness since, if policing technology has an encouraging effect on citizens to report more crime, as discussed in Chapter 2, then clearance rates will relatively decrease (Garicano & Heaton, 2006, p. 3). In such a case clearance rate (number of clearance divided by number of crimes) will not be a good measure of police effectiveness. Therefore number of total, violent and property crime clearances by arrest measures used in this research are taken as direct measures of police effectiveness only controlled for jurisdiction size.

The demographic control variables include unemployment, percentage of population between the ages of 13 and 24, percentage of high school graduates,
percentage of population living in urban areas, percentage of males, percentage of African-Americans, percentage of people with income below poverty level, percentage of renters, percentage of single female households and population density.

Before delving into the analyses and description of the variables, I will provide brief explanations as to why certain variables have been chosen as control variables. It should be noted that most of the control variables included in the models are mainly derived from criminological or crime theories. Since those theories strive to explain the phenomenon of crime and the dependent variable in this part is crime clearances, which is a correlate of crime, whatever explanations brought forth by mainstream crime theories should be incorporated into any model that explains the variation in correlates of crime.

The literature suggests that crimes are mostly committed by people between the ages 13 and 24 and then start to decrease as the age increases (Farrington, 1986). Therefore a measure of age is included in the models. According to Merton (2003) and Messner and Rosenfeld (2003) when social institutions such as the family are weak in developing the social norms anomie or normlessness ensues, causing higher crime rates. On the other hand, due to lack of collective efficacy communities become disorganized (Robert J. Sampson, et al., 2003; Shaw & McKay, 2003) and when informal social control mechanisms (social bonds and self control) do not operate efficiently (Gottfredson & Hirschi, 2003; Hirschi, 2003; Reckless, 2003) criminal behavior occurs. Thus measures of broken families (single female household, percent married population) and social disorganization (percent renters, percent living in urban areas) are added in the models. There are also theories that argue that males are more likely than females to
engage in crime (Messerschmitt, 2003) and racial minorities especially African-Americans are more likely to engage in crime (Anderson, 2003; Robert J. Sampson & Wilson, 2003).

As stated in the theoretical basis section above, the rationale behind the relationship between police effectiveness and policing technology (in this study measured by crime analysis and crime mapping) is that those tools enable the police to be present at appropriate places at the appropriate times. This increases the likelihood of the presence of a capable guardian, which is the third necessary component of a criminal event apart from a motivated offender and a suitable target according to routine activity theory (Cohen & Felson, 2003). Another theoretical argument about the effect of police on crime is deterrence. While both the classical and the modern deterrence theories mainly focus on punishment and punishment avoidance on general and specific levels (Cornish & Clarke, 1986; Stafford & Warr, 1993), punishment is not possible without an arrest. Therefore number of clearances is taken in this study as both measures of police effectiveness and deterrence.

The main explanatory variables are different measures of crime mapping and crime analysis use, which are explained in detail below.

In order to operationalize crime analysis, an index variable has been created using various indicators. In CCMLE survey the police departments were asked the types of crime mapping analyses they employ within the department. These crime analysis methods were measured for reliability in order to create an index variable, which is a composite measure to capture the variation in types of crime analysis techniques used in
the department. The crime analysis types index is made up of following questions; (1) Point pattern analysis, (2) Pin maps, (3) Trend analyses, (4) UCR reports, (5) Case studies, (6) Incident recaps, (7) Statistical reports, (8) Case management, (9) Linkage analysis, (10) Pattern detection, and (11) Strategic/situational analysis. The Cronbach’s alpha value (scale reliability coefficient) for the index is 0.709. Although there is no certain cut-off point that is agreed upon for Cronbach’s alpha, the generally accepted minimum value is .7 (Chatterjee, et al., 2000). Based on this criterion the use of crime analysis index, which was created by summing the crime analysis methods across the departments, is a reliable measure of crime analysis use in police departments.

In CCMLE survey the police departments were asked the types of crimes the department maps and the frequency of conducting crime mapping analyses. In order to operationalize crime mapping use, a composite measure of the crime types that are mapped has been created. Also a measure of how often crime mapping is used by the department has been included in the data analysis.

The mapped crimes index is composed of the following types of crimes that are mapped; (1) Robbery, (2) homicide, (3) rape, (4) aggravated assault, (5) common assault, (6) disorderly conduct, (7) burglary, (8) larceny-theft, (9) motor vehicle, (10) theft, (11) arson, (12) weapons violations, (13) gangs, (14) drug offenses, (15) domestic violence, (16) traffic offenses, (17) forgery/fraud, (18) firearm discharges, (19) vandalism, (20) gambling, (21) kidnapping, (22) prostitution, (23) other sex offenses, and (24) driving under influence. This index is a measure of how extensively the departments map crimes. The Cronbach’s alpha value (scale reliability coefficient) for the index is 0.95,
thus this index is a reliable measure of extensive mapping of crime types in police
departments. In creating the variable all the indicators were summed across the police
departments.

In the CCMLE survey, the departments were asked several questions on how
often they do crime mapping. Those questions were recoded into a single variable in
order to create the frequency of crime mapping use variable. Frequency of crime mapping
use ranges from “0” to “5”, where the highest value “5” indicates daily use of crime
mapping and the lowest value “0” indicates occasional use of crime mapping. The value
“4” indicates weekly use of crime mapping. “3” indicates bi-weekly use of crime
mapping. “2” indicates monthly use of crime mapping. And, “1” indicates irregular use of
crime mapping mostly when necessary.

Department level control variables are incident based records index, sworn
personnel, whether AFIS (Automated Fingerprint Identification System) is used, percent
community policing officers and whether patrols are assigned to certain predetermined
geographic beats.

The incident based records were measured for reliability in order to create an
index variable, which is a composite measure to capture the intensity of records kept for
crime analysis. The incident based records index is made up of following questions; (1)
Robbery incident-based record, (2) Homicide incident-based record, (3) Rape incident-
based record, (4) Aggravated assault incident-based record, (5) Common assault incident-
based record, (6) Disorderly conduct incident-based record, (7) Burglary incident-based
record, (8) Larceny incident-based record, (9) Motor vehicle theft incident-based record,
(10) Arson incident-based record, (11) Weapons incident-based record, (12) Gangs incident-based record, (13) Drugs incident-based record, (14) Domestic violence incident-based record, (15) Traffic offences incident-based record, (16) Forgery incident-based record, (17) Vandalism incident-based record, (18) Firearms incident-based record, (19) Gambling incident-based record, (20) Kidnapping incident-based record, (21) Prostitution incident-based record, (22) Sex offenses incident-based record, and (23) DUI (driving under influence) / DWI (driving while intoxicated) incident-based record. The Cronbach’s alpha value (scale reliability coefficient) for the index is 0.987, thus this index is a reliable measure of extensive record keeping of crime types in police departments. This variable was also created by summing the factors.

The basic descriptive statistics for the variables used in this section are given in Table 9.
Table 9 Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Crime Clearance</td>
<td>1713</td>
<td>3.96</td>
<td>5.17</td>
<td>0.00</td>
<td>38.89</td>
</tr>
<tr>
<td>Violent Crime Clearance</td>
<td>1713</td>
<td>2.41</td>
<td>3.68</td>
<td>0.00</td>
<td>35.39</td>
</tr>
<tr>
<td>Property Crime Clearance</td>
<td>1713</td>
<td>1.55</td>
<td>2.36</td>
<td>0.00</td>
<td>31.99</td>
</tr>
<tr>
<td><strong>Explanatory Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency of Mapping</td>
<td>1825</td>
<td>0.38</td>
<td>1.12</td>
<td>0.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Crime Analysis Index</td>
<td>1581</td>
<td>3.05</td>
<td>2.21</td>
<td>1.00</td>
<td>11.00</td>
</tr>
<tr>
<td>Mapped Crimes Index</td>
<td>1764</td>
<td>1.71</td>
<td>4.88</td>
<td>0.00</td>
<td>23.00</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Crimes</td>
<td>1713</td>
<td>10.26</td>
<td>12.47</td>
<td>0.00</td>
<td>115.38</td>
</tr>
<tr>
<td>Violent Crimes</td>
<td>1713</td>
<td>0.45</td>
<td>1.41</td>
<td>0.00</td>
<td>40.57</td>
</tr>
<tr>
<td>Property Crimes</td>
<td>1713</td>
<td>9.81</td>
<td>11.74</td>
<td>0.00</td>
<td>115.38</td>
</tr>
<tr>
<td>Total Population</td>
<td>1825</td>
<td>110,206.20</td>
<td>348,338.00</td>
<td>83.00</td>
<td>8,008,278.00</td>
</tr>
<tr>
<td>Sworn Officers</td>
<td>1722</td>
<td>2.48</td>
<td>4.35</td>
<td>0.00</td>
<td>123.08</td>
</tr>
<tr>
<td>Incident-based Records</td>
<td>1330</td>
<td>20.05</td>
<td>4.79</td>
<td>1.00</td>
<td>23.00</td>
</tr>
<tr>
<td>AFIS use</td>
<td>1825</td>
<td>0.18</td>
<td>0.38</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Percent Unemployed</td>
<td>1825</td>
<td>0.03</td>
<td>0.01</td>
<td>0.00</td>
<td>0.19</td>
</tr>
<tr>
<td>Age Between 13 &amp; 24</td>
<td>1825</td>
<td>9.93</td>
<td>2.10</td>
<td>0.00</td>
<td>34.43</td>
</tr>
<tr>
<td>Education</td>
<td>1825</td>
<td>52.53</td>
<td>8.39</td>
<td>14.94</td>
<td>84.56</td>
</tr>
<tr>
<td>Percent Urban</td>
<td>1825</td>
<td>70.16</td>
<td>38.63</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Percent Male</td>
<td>1825</td>
<td>48.66</td>
<td>2.61</td>
<td>38.26</td>
<td>82.34</td>
</tr>
<tr>
<td>Percent African American</td>
<td>1825</td>
<td>9.92</td>
<td>15.59</td>
<td>0.00</td>
<td>93.31</td>
</tr>
<tr>
<td>Percent Below Poverty</td>
<td>1825</td>
<td>12.25</td>
<td>7.06</td>
<td>0.35</td>
<td>54.86</td>
</tr>
<tr>
<td>Percent Single Female</td>
<td>1825</td>
<td>2.68</td>
<td>1.20</td>
<td>0.00</td>
<td>8.13</td>
</tr>
<tr>
<td>Percent Renter</td>
<td>1825</td>
<td>12.30</td>
<td>5.42</td>
<td>0.80</td>
<td>52.17</td>
</tr>
<tr>
<td>Population Density</td>
<td>1825</td>
<td>1,765.89</td>
<td>2,525.69</td>
<td>0.39</td>
<td>30,210.16</td>
</tr>
<tr>
<td>Community Policing</td>
<td>1330</td>
<td>3.97</td>
<td>8.54</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Geographic Patrol</td>
<td>1330</td>
<td>0.78</td>
<td>0.42</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>Instrument Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education Requirement</td>
<td>1330</td>
<td>1.29</td>
<td>0.70</td>
<td>0.00</td>
<td>4.00</td>
</tr>
<tr>
<td>Body Armor Supplied</td>
<td>1330</td>
<td>0.89</td>
<td>0.31</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Selection Methods</td>
<td>1330</td>
<td>8.67</td>
<td>1.83</td>
<td>0.00</td>
<td>11.00</td>
</tr>
<tr>
<td>Computer Training</td>
<td>1713</td>
<td>0.10</td>
<td>0.30</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Analysis

One of the most common methods used in cases of reciprocal causality is two stages least squares method, in which endogenous independent variables are estimated using instrumental variables in the first stage and then included in the model to estimate the endogenous dependent variable in the second model. In the two stages least squares method, there should be at least as many instrument variables as the number of instrumented (endogenous independent) variables.

An instrument should be highly correlated, either negatively or positively, with the endogenous independent (explanatory) variable, and should be uncorrelated with the dependent variable, and the error term. In other words, the instrument variable should be uncorrelated with potential factors that affect the dependent variable that are not in the model. That is, the instrument variable should not be correlated with any possible explanations of the dependent variable that are present in the error term as omitted variables or measurement errors. This last requirement is very hard to check or even test since the requirement asserts that the covariance between the instrument variable and the unobservable error term is zero. This requirement is generally met via gut feeling, common sense, and theoretical assumptions of behavior, whereas the other requirements can be tested in the data (Wooldridge, 2002).

Therefore, as instrument variables several variables were used in the analyses; education requirement for newly recruited officers, whether body armor is supplied by the department, number of selection methods employed by the department for recruiting
new officers and whether officers that do crime mapping had informal computer training before they were recruited to the force.

The instrument variables used in the models have been chosen since they theoretically meet the above mentioned criteria and some have been used in a similar study (Garicano & Heaton, 2006, p. 17) to test the effect of information technology on police capabilities. Informal computer training measures whether the officers using computers in the department have self-taught crime mapping knowledge. Theoretically this has no relationship with crime or determinants of crime. Body armor is a weaker instrument than informal computer training, yet it theoretically makes sense to include in the model since it is a measure of capital capability of a department to buy crime mapping equipment. Since body armors are expensive equipments, only police departments with large resources would be able to spare funds for such substantial expenditures. And such departments are more likely to adopt crime analysis and crime mapping technology. Educational requirement and variation in selection methods for new recruits also measure capital and human resource capabilities of departments.

As mentioned above, treating a variable as exogenous, when it really should be endogenous because there is some feedback, will result in biased and inconsistent parameter estimates. Also in cases where there is no endogeneity and the model is treated as such, we lose hypothesis testing as in the case of heteroskedasticity (Wooldridge, 2002). In that sense, test of endogeneity (Durbin, 1954; Hausman, 1978; Wu, 1973) was conducted in order to see if there is a feedback effect with the models using potential instruments available in the data.
The endogeneity test performed in Stata (using `ivendog` command after two-stage least squares estimation using `ivreg2` command) tests the null hypothesis “that an ordinary least squares (OLS) estimator of the same equation would yield consistent estimates; that is, any endogeneity among the regressors would not have deleterious effects on OLS estimates” (StataCorp, 2007, p. 1). If the null hypothesis is rejected instrument variables should be used. With Durbin-Wu-Hausman test, the hypothesis testing is based on a chi-squared statistics “with m degrees of freedom, where m is the number of regressors specified as endogenous in the original IV regression” (StataCorp, 2007, p. 1). Also a supplementary F statistics as proposed by Wu and Hausman (StataCorp, 2007, p. 1) is given to obtain more rigorous results.

The results of the endogeneity tests are given in Table 10.
Table 10 Exogeneity Test Results for All Models

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable:</strong></td>
<td><strong>Total Number of Clearances per 1,000 Population</strong></td>
<td><strong>Violent Crime Clearances per 1,000 Population</strong></td>
<td><strong>Property Crime Clearances per 1,000 Population</strong></td>
</tr>
<tr>
<td><strong>Instrument Variables</strong></td>
<td>Education Requirement</td>
<td>Body Armor Supplied</td>
<td>Education Requirement</td>
</tr>
<tr>
<td><strong>Endogenous Variables</strong></td>
<td>Frequency of Mapping</td>
<td>Frequency of Mapping</td>
<td>Frequency of Mapping</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td>Crime Analysis Index</td>
<td>Crime Analysis Index</td>
<td>Crime Analysis Index</td>
</tr>
<tr>
<td><strong>Variables</strong></td>
<td>Mapped Crimes Index</td>
<td>Mapped Crimes Index</td>
<td>Mapped Crimes Index</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wu-Hausman F-test</strong></td>
<td>1.47420 F (3,492)</td>
<td>2.18144 F (3,492)</td>
<td>1.18212 F (3,492)</td>
</tr>
<tr>
<td><strong>P-value</strong></td>
<td><strong>0.22071</strong></td>
<td><strong>0.08936</strong></td>
<td><strong>0.31597</strong></td>
</tr>
<tr>
<td><strong>Durbin-Wu-Hausman Chi-sq test</strong></td>
<td>4.58811 Chi-sq(3)</td>
<td>6.76034 Chi-sq(3)</td>
<td>3.68557 Chi-sq(3)</td>
</tr>
<tr>
<td><strong>P-value</strong></td>
<td><strong>0.20456</strong></td>
<td><strong>0.07994</strong></td>
<td><strong>0.29748</strong></td>
</tr>
</tbody>
</table>

H₀: Regressors are exogenous
No endogeneity problem was found as a result of the tests in Table 9 since in none of the models the null hypothesis that the regressors are exogenous could be rejected. Therefore, I performed regular regression analysis in order to test the research hypotheses as explained below.

Before deciding on the final models, regular multiple regression diagnostics for outliers, non-linearity, heteroskedasticity, and multi-collinearity were completed using appropriate procedures.\(^9\) Percentage of single female households and percentage of population between 13 and 24 ages were not included in the analyses due to high collinearity.\(^10\)

All models in Table 10, where the dependent variables are total crime clearances, violent crime clearances and property crime clearances have satisfactory joint significance with F statistics values significant at .001 alpha level. In those models crime rates were included in each model accordingly as explanatory variables in order to avoid spuriousness since crime rates are probably the most obvious indicator of crime clearances as the latter cannot be without the former. In fact in all three models crime rates are highly significant predictors of crime clearances with an alpha level of p<.001.

\(^9\) No influential cases were detected in all of the models. Partial regression plots revealed linearity in models. As mentioned in tables robust standard errors were estimated to correct for heteroskedasticity.

\(^10\) In cases when the variance inflation factor (VIF) is less than 10 and/or the tolerance (1/VIF) is larger than .1, no multi-collinerarity is assumed (Belsley, et al., 1980; Greene, 2003).
Table 11 Regression Analysis of Clearance Rates

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Model -1 Total Crime Clearances</th>
<th>Model -2 Violent Crime Clearances</th>
<th>Model -3 Property Crime Clearances</th>
</tr>
</thead>
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<tr>
<td>Frequency of Mapping</td>
<td>-0.03 (0.14)</td>
<td>0.09 (0.1)</td>
<td>-0.07 (0.07)</td>
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<tr>
<td>Crime Analysis Index</td>
<td>0.21** (0.07)</td>
<td>-0.01 (0.02)</td>
<td>0.10** (0.04)</td>
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<tr>
<td>Mapped Crimes Index</td>
<td>-0.01 (0.03)</td>
<td>-0.02 (0.02)</td>
<td>0.00 (0.02)</td>
</tr>
</tbody>
</table>

| Control Variables     |                                 |                                   |                                   |
|-----------------------|                                 |                                   |                                   |
| Total Crimes          | 0.36*** (0.02)                  |                                   |                                   |
| Violent Crimes        |                                 | 3.47*** (0.21)                    |                                   |
| Property Crimes       |                                 |                                   | 0.11*** (0.01)                    |
| Total Population      | 0.00 (0.00)                     | 0.01** (0.001)                    | 0.00 (0.00)                      |
| Sworn Officers        | 0.07* (0.03)                    | 0.01 (0.03)                       | 0.03* (0.01)                     |
| Incident-based Records| -0.01 (0.03)                    | 0.01 (0.001)                      | 0.01 (0.01)                      |
| AFIS use              | 0.72* (0.3)                     | 0.29 (0.25)                       | 0.08 (0.16)                      |
| Percent Unemployed    | -4.83 (18.32)                   | 16.79 (14.21)                     | -10.73 (12.51)                   |
| Education             | -0.07* (0.03)                   | -0.01 (0.03)                      | -0.02 (0.02)                     |
| Percent Urban         | -0.01 (0.01)                    | 0.01* (0.004)                     | 0.01 (0.01)                      |
| Percent Male          | -0.08 (0.1)                     | 0.12 (0.09)                       | -0.19*** (0.06)                  |
| Percent African American| 0.01 (0.01)                   | -0.04*** (0.01)                   | 0.001 (0.01)                     |
| Percent Below Poverty | -0.06 (0.05)                    | 0.07 (0.04)                       | -0.01 (0.03)                     |
| Percent Renter        | 0.02 (0.04)                     | -0.05 (0.03)                      | 0.05** (0.02)                    |
| Population Density    | 0.001*** (0.0001)               | 0.01 (0.001)                      | 0.001 (0.01)                     |
| Community Policing    | -0.03 (0.03)                    | 0.02 (0.03)                       | -0.01 (0.01)                     |
| Geographic Patrol     | 0.28 (0.3)                      | 0.46 (0.32)                       | 0.04 (0.21)                      |

| Constant              | 4.79 (6.17)                     | -4.04 (5.41)                      | 7.54 (4.04)                      |

| N                     | 978                             | 978                               | 978                               |
| F                     | 57.25***                        | 49.99***                          | 22.11***                          |
| R²                    | 0.77                            | 0.76                              | 0.52                              |

Significance levels based on a one-tailed test: *** p < .001, ** p < .01, * p < .05. Robust standard errors in parenthesis.
In models 1 and 3 crime analysis index is significantly correlated with the dependent variable. Also the relationships are in positive direction as expected. In other words, as the number of crime analysis functions of the department increase, the effectiveness of the department in terms of more number of total and property crime clearances per 1,000 population also increases. The other explanatory variables, frequency of crime mapping and number of mapped crimes are not significant estimators of the dependent variable.

Also in models 1 and 3 sworn officers is significantly and positively correlated with the dependent variable. That is, as the number of sworn officers in the department increases, the number of total and property crime clearances per 1,000 population also increases. Another department level control variable, AFIS use, is also significantly and positively correlated with total clearance rates in Model 1. This suggests that use of automated fingerprint identification system increases number of total clearances.

**Panel Data Analysis**

As both an alternative and supplementary to the cross-sectional data analysis, a series of *static-score panel model* data analyses have also been employed to overcome the problem of endogeneity inherent in the relationship between crime and policing technology. Naturally “observing the same units over time leads to several advantages over cross-sectional data” since “having multiple observations on the same units allows us to control certain unobserved characteristics” of our unit of analysis (Wooldridge, 2002, p. 13). Panel data also allows the researcher to make causal inferences in situations
where causal inference is very hard to make. Panel data makes it possible to examine the change of effects over time since many actions or causes have an impact only after some time has passed (Wooldridge, 2002, p. 13) and this is an important aspect of causality that cannot be captured with cross sectional data. Last but not least, panel data has certain advantages over cross-sectional analyses in determining causal effects between reciprocally affecting variables since incorporation of outside variables (instrument variables) with restrictive and hard to meet assumptions is not necessary with panel data (Finkel, 1995, p. 23).

The CCMLE data is cross sectional data and is not available over time. However, the LEMAS data, UCR data and Census data are available over time with some limitations. LEMAS data is available in irregular intervals between 1987 and 2003, UCR is available for all years in between and Census is available only for 1990 and 2000.

The data set created to do the panel data analysis is constructed like a pooled cross section data but only departments that have responded to all LEMAS surveys were taken. Therefore, it essentially has a panel data structure since the same observations are repeated over time (Wooldridge, 2002, p. 10).

In order to fill the missing data on Census based variables, linear interpolation was used. Linear interpolation examines the values on a variable across a span and recognizing the pattern of the data, the technique provides the researcher, in conformity with the pattern of the data, with substitute values for the missing values (De Vaus, 2002, p. 69).
Variables

As with the cross-sectional analysis the dependent variables in this part are per 1,000 population clearance rates (total, violent and property) as measures of police effectiveness.

The main explanatory variables are two dichotomous variables; crime analysis and crime mapping. Each variable is a measure of whether the department has crime analysis or crime mapping. Also the change in crime analysis and crime mapping use are calculated and used as explanatory variables in the statistical analyses.

The demographic control variables include population density, percentage of high school graduates, percentage of population living in urban areas, percentage of males, percentage of African-Americans, percentage of people with income below poverty level, and percentage of renters.

Department level control variables include agency functions index, automated fingerprint identification (AFIS), number of sworn officers per 1,000 population, percent community policing officers, and whether patrols are assigned to certain predetermined geographic beats. All control variables are department level functions that would affect crime solving capabilities of the department and thus included in the analysis to avoid spuriousness.

All department level control variables were standardized for each year. Therefore, for those measures standardized scores were used in the variables and the variation in those variables is in standard deviation units.

One of the survey questions asked to the police departments in LEMAS is
whether they have several important functions. These functions were measured for reliability in each year in order to create an index of police services\textsuperscript{11}. Although some functions were not asked in some years, the standardization of each variable in each year ensures the stability of the measure over time. The following functions were added into a single variable to create a composite measure of agency functions for the year 2003: (1) Enforcement of traffic laws, (2) Traffic direction and control, (3) Accident investigation, (4) Dispatching calls for service, (5) Vice enforcement, (6) Fingerprint processing, (7) Ballistics testing, (8) Crime lab services, (9) Bomb disposal, (10) Search and rescue, (11) School crossing services, (12) Tactical operations, (13) Parking enforcement, (14) Executing arrest warrants, (15) Court security, (16) Jail operations, (17) Civil defense, (18) Homicide investigations, (19) Other violent crime investigation, (20) Arson investigations, (21) Other property crime investigation, (22) Environmental crime investigation, and (23) Primary drug enforcement. The index was created by summing the survey questions. These functions indicate the capabilities and resources of police departments, thus the index variable measures the overall functionality of the police department, which would enhance the departments’ crime solving capacity.

Table 12 provides the descriptive statistics of the variables used in the panel data analysis.

\textsuperscript{11} Cronbach’s Alpha for agency functions index in year 2003 is .922, in year 2000 it is .897, in year 1997 it is .917, in year 1993 it is .878, in year 1990 it is .824 and in year 1987 it is .948.
<table>
<thead>
<tr>
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<th>N</th>
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<th>Std. Dev.</th>
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</table>
Analysis

For the panel data analysis, I have created static score models with both lagged and instantaneous effects. The logic of creating a lagged and instantaneous effect model is to include the independent variable measured at previous wave(s) \( (X_{t-1}) \) and the change in the independent variable over time \( (\Delta X = X_t - X_{t-1}) \). Also, in order to capture the effect of the independent variable on the change in the dependent variable over time, in estimating the dependent variable at present wave \( (Y_t) \), the dependent variable measured at the previous wave \( (Y_{t-1}) \) is also included in the models. Finkel (1995, p. 14) shows that this approach is equal algebraically, yet superior in terms of its specifications, to estimating the change in the dependent variable over time \( (\Delta Y = Y_t - Y_{t-1}) \).

Before specifying the whole models in formula and presenting the results of the analysis, I want to provide a concise and generic form of the regression formula below in order to make the logic behind creating these models more understandable.

\[
Y_t = \beta_0 + \beta_1 X_t + \beta_2 Y_{t-1} + \beta_3 X_{t-1} + \varepsilon_t
\]

**Equation 8 Static Score Panel Model Formula 1**

This formula can be algebraically manipulated and both the change in the dependent variable \( (Y) \) and the change in the independent variable \( (X) \) can be incorporated in the model.

By substituting;

\[
\Delta Y = Y_t - Y_{t-1}
\]
\[ \Delta X = X_t - X_{t-1}, \] \hspace{1cm} \text{Equation 1}\]

It can be shown that the formula in Equation 1 is equal\(^{13}\) to the formulas given in Equation 4 and Equation 5;

\[ Y_t = \beta_0 + (\beta_1 + \beta_3) X_t + \beta_2 Y_{t-1} - \beta_3 \Delta X + \epsilon_t \]

\text{Equation 9 Static Score Panel Model Formula 2}

\[ \Delta Y = \beta_0 + (\beta_1 + \beta_3) X_t + (\beta_2 - 1) Y_{t-1} - \beta_3 \Delta X + \epsilon_t \]

\text{Equation 10 Static Score Panel Model Formula 3}

In the statistical models I have created for the static score panel data analysis in this research, I use the formula given in Equation 4;

\[ Y_t = \beta_0 + (\beta_1 + \beta_3) X_t + \beta_2 Y_{t-1} - \beta_3 \Delta X + \epsilon_t \]

In this algebraic manifestation of a static score panel model or the conditional change panel model, \( (\beta_1 + \beta_3) \) is the effect of the independent variable measured at the last wave (instantaneous effect) and \( \beta_3 \) is the effect of change in the independent variable from the previous wave to the last wave (lagged effect) on the change in the dependent

\(^{12}\) Also, \( X_{t,1} = X_t - \Delta X \)

\(^{13}\) \( Y_t = \beta_0 + \beta_1 X_t + \beta_2 Y_{t-1} + \beta_3 X_{t-1} + \epsilon_t \)

Substituting \( X_{t,1} \) with \( X_t - \Delta X \)

\( Y_t = \beta_0 + \beta_1 X_t + \beta_2 Y_{t-1} + \beta_3 (X_t - \Delta X) + \epsilon_t \)

\( Y_t = \beta_0 + \beta_1 X_t + \beta_2 Y_{t-1} + \beta_3 X_t - \beta_3 \Delta X + \epsilon_t \)

\( Y_t = \beta_0 + (\beta_1 + \beta_3) X_t + \beta_2 Y_{t-1} - \beta_3 \Delta X + \epsilon_t \)

Subtracting \( Y_{t-1} \) from both sides of the equation

\( Y_t - Y_{t-1} = \beta_0 + (\beta_1 + \beta_3) X_t + \beta_2 Y_{t-1} - \beta_3 \Delta X + \epsilon_t \)

\( \Delta Y = \beta_0 + (\beta_1 + \beta_3) X_t + (\beta_2 - 1) Y_{t-1} - \beta_3 \Delta X + \epsilon_t \)
variable from the previous wave to the last wave.

The logic behind the inclusion of the change in the independent variable over time can be better understood by an examination of Figures 20 and 21, in which the change in the number of crime analysis and crime mapping adopters is given. As can be seen from the graphs, while some departments that did not use crime mapping or crime analysis in 1997 start to use or continue to use those technologies, some discontinue and quit using those technologies. Therefore, it is important to capture the effect of this change in behavior by adding the change variables in the analyses.

Figure 20 Change in the Number of Crime Analysis Users from 1997 to 2003
Based on the explanations above, I have constructed a total of nine static score models to test the research hypothesis. In the models total crime clearances, violent crime clearances and property crime clearances are the dependent variables respectively for years 1999, 2000 and 2003.

**Panel Models for Total Crime Clearances**

In order to test the impact of crime analysis and crime mapping use on changes in total crime clearances over time the year 1997 is taken as the first wave and the changes in total crime clearances are estimated based on the changes in crime analysis and crime mapping adoption. There are three models in this part of the research.

The first model is illustrated in the regression equation in Equation 11.
\[ Y_{\text{total cleared crime 2003}} = \beta_0 + \beta_1 Y_{\text{total cleared crime 1997}} + \beta_2 X_{\text{total crimes 2003}} + \beta_3 X_{\text{crime analysis 2003}} + \beta_4 \Delta X_{\text{crime analysis}} + \beta_5 X_{\text{crime mapping 2003}} + \beta_6 \Delta X_{\text{crime mapping}} + \beta_7 X_{\text{population density 2003}} + \beta_8 X_{\text{education 2003}} + \beta_{10} X_{\text{urban percentage 2003}} + \beta_{11} X_{\text{percent male 2003}} + \beta_{12} X_{\text{percent black 2003}} + \beta_{13} X_{\text{percent below poverty 2003}} + \beta_{14} X_{\text{percent renters 2003}} + \beta_{15} X_{\text{sworn 2003}} + \beta_{16} X_{\text{AFIS use 2003}} + \beta_{17} X_{\text{agency functions 2003}} + \beta_{18} X_{\text{geographic assignment 2003}} + \beta_{19} X_{\text{community policing officers 2003}} + \epsilon \]

Equation 11 Regression Formula for Estimating Total Crime Clearances in 2003

In this first model, the dependent variable is the change in total crime clearances from year 1997 to 2003. The main explanatory variables are crime analysis and crime mapping use in 2003 and changes in crime analysis and crime mapping use from 1997 to 2003. Referring back to the hypothesis statement, the expected sign of \( \beta_3, \beta_4, \beta_5, \) and \( \beta_6 \) are positive and the expected values of the coefficients under the alternative hypothesis are:

\[ H_A; \beta_3>0, \beta_4>0, \beta_5>0 \text{ and } \beta_6>0 \]

The second model is illustrated in the regression equation in Equation 12.

\[ Y_{\text{total cleared crime 2000}} = \beta_0 + \beta_1 Y_{\text{total cleared crime 1997}} + \beta_2 X_{\text{total crimes 2000}} + \beta_3 X_{\text{crime analysis 2000}} + \beta_4 \Delta X_{\text{crime analysis}} + \beta_5 X_{\text{crime mapping 2000}} + \beta_6 \Delta X_{\text{crime mapping}} + \beta_7 X_{\text{population density 2000}} + \beta_8 X_{\text{education 2000}} + \beta_{10} X_{\text{urban percentage 2000}} + \beta_{11} X_{\text{percent male 2000}} + \beta_{12} X_{\text{percent black 2000}} + \beta_{13} X_{\text{percent below poverty 2000}} + \beta_{14} X_{\text{percent renters 2000}} + \beta_{15} X_{\text{sworn 2000}} + \beta_{16} X_{\text{AFIS use 2000}} + \beta_{17} X_{\text{agency functions 2000}} + \beta_{18} X_{\text{geographic assignment 2000}} + \beta_{19} X_{\text{community policing officers 2000}} + \epsilon \]

Equation 12 Regression Formula for Estimating Total Crime Clearances in 2000

In the second model, the dependent variable is the change in total crime clearances from year 1997 to 2000. The main explanatory variables are crime analysis and crime mapping use in 2000 and changes in crime analysis and crime mapping use from 1997 to 2000. Referring back to the hypothesis statement, the expected sign of \( \beta_3, \beta_4, \beta_5, \) and \( \beta_6 \) are positive and the expected values of the coefficients under the alternative hypothesis are;
The third model is illustrated in the regression equation in Equation 13.

\[ Y_{\text{total cleared crime 1999}} = \beta_0 + \beta_1 Y_{\text{total cleared crime 1997}} + \beta_2 X_{\text{total crimes 1999}} + \beta_3 X_{\text{crime analysis 1999}} + \beta_4 \Delta X_{\text{crime analysis}} + \beta_5 X_{\text{crime mapping 1999}} + \beta_6 \Delta X_{\text{crime mapping}} + \beta_7 X_{\text{population density 1999}} + \beta_8 X_{\text{education 1999}} + \beta_9 X_{\text{urban percentage 1999}} + \beta_{10} X_{\text{percent male 1999}} + \beta_{11} X_{\text{percent black 1999}} + \beta_{12} X_{\text{percent below poverty 1999}} + \beta_{13} X_{\text{percent renters 1999}} + \beta_{14} X_{\text{sworn 1999}} + \beta_{15} X_{\text{agency functions 1999}} + \beta_{16} X_{\text{geographic assignment 1999}} + \beta_{17} X_{\text{community policing officers 1999}} + \varepsilon \]

Equation 13 Regression Formula for Estimating Total Crime Clearances in 1999

In the last model, the dependent variable is the change in total crime clearances from year 1997 to 1999. The main explanatory variables are crime analysis and crime mapping use in 1999 and changes in crime analysis and crime mapping use from 1997 to 1999. Referring back to the hypothesis statement, the expected sign of \( \beta_3, \beta_4, \beta_5, \text{ and } \beta_6 \) are positive and the expected values of the coefficients under the alternative hypothesis are;

\[ H_A; \beta_3>0, \beta_4>0, \beta_5>0 \text{ and } \beta_6>0 \]

Since AFIS use was not asked in LEMAS 1999 survey, this department level control variable was not added in this model.

The regression results of all three models are given in Table 13.

According to the F test results, all three models have joint significance in predicting the dependent variable. Besides, the goodness of fit statistics (R-squared) signifies that in all models at least 65% of the variation in the dependent variable is explained by the models.
### Table 13: Static-Score Panel Models for Total Crime Clearances

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Crime Analysis Change</td>
<td>0.16 (1.62)</td>
<td>0.60 (1.81)</td>
<td>-0.56 (1.79)</td>
</tr>
<tr>
<td>Crime Mapping Change</td>
<td>-1.07 (1.42)</td>
<td>-1.57 (1.06)</td>
<td>0.23 (1.2)</td>
</tr>
<tr>
<td>Crime Analysis</td>
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<td>-0.69 (2.34)</td>
<td>-1.05 (2.58)</td>
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<tr>
<td>Crime Mapping</td>
<td>-0.67 (1.36)</td>
<td>3.04* (1.61)</td>
<td>3.22* (1.9)</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Clearance in 1997</td>
<td>0.42*** (0.06)</td>
<td>0.35*** (0.07)</td>
<td>0.29*** (0.07)</td>
</tr>
<tr>
<td>Total Crime</td>
<td>0.15*** (0.03)</td>
<td>0.15*** (0.04)</td>
<td>0.19*** (0.03)</td>
</tr>
<tr>
<td>Population Density</td>
<td>0.00 (0.00)</td>
<td>-0.00* (0.00)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>Education</td>
<td>0.02 (0.12)</td>
<td>-0.13 (0.14)</td>
<td>-0.2 (0.11)</td>
</tr>
<tr>
<td>Percent Urban</td>
<td>0.21 (0.21)</td>
<td>0.4 (0.36)</td>
<td>0.22 (0.13)</td>
</tr>
<tr>
<td>Percent Male</td>
<td>0.45 (0.3)</td>
<td>-0.3 (0.33)</td>
<td>-0.22 (0.19)</td>
</tr>
<tr>
<td>Percent African American</td>
<td>-0.05 (0.03)</td>
<td>-0.09* (0.03)</td>
<td>-0.06 (0.12)</td>
</tr>
<tr>
<td>Percent Below Poverty</td>
<td>0.01 (0.2)</td>
<td>-0.12 (0.25)</td>
<td>-0.64* (0.3)</td>
</tr>
<tr>
<td>Percent Renter</td>
<td>-0.12 (0.14)</td>
<td>0.14 (0.17)</td>
<td>0.4 (0.32)</td>
</tr>
<tr>
<td>Sworn Officers</td>
<td>1.95*** (0.52)</td>
<td>1.15* (0.62)</td>
<td>2.44*** (0.87)</td>
</tr>
<tr>
<td>AFIS use</td>
<td>-0.05 (0.65)</td>
<td>0.06 (0.64)</td>
<td>-0.05 (0.64)</td>
</tr>
<tr>
<td>Agency Functions Index</td>
<td>-0.65 (0.52)</td>
<td>-0.19 (0.52)</td>
<td>-0.58 (0.56)</td>
</tr>
<tr>
<td>Geographic Patrol</td>
<td>0.1 (0.45)</td>
<td>-0.77 (0.59)</td>
<td>-0.02 (0.56)</td>
</tr>
<tr>
<td>Community Policing</td>
<td>0.37 (0.45)</td>
<td>1.08* (0.51)</td>
<td>0.4 (0.46)</td>
</tr>
<tr>
<td>Constant</td>
<td>-41.44 (27.79)</td>
<td>-18.17 (43.03)</td>
<td>3.86 (11.11)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>214</td>
<td>215</td>
<td>215</td>
</tr>
<tr>
<td><strong>F</strong></td>
<td>90.48***</td>
<td>116.85***</td>
<td>21.21***</td>
</tr>
<tr>
<td><strong>R^2</strong></td>
<td>0.75</td>
<td>0.65</td>
<td>0.68</td>
</tr>
</tbody>
</table>

Significance levels based on a one-tailed test: *** p < .001, ** p < .01, * p < .05. Robust standard errors in parenthesis.
Among the explanatory variables only crime mapping use is significant in two of the models. Crime mapping use has a statistically significant and positive instantaneous effect on the change in total crime clearances from 1997 to years 2000 (Model 2) and 2003 (Model 3) since the coefficients for this variable in both models is significant at .05 alpha level. In other words, current use of crime mapping increases total crime clearances over time.

In all three models, the number of sworn officers per 1,000 population variable is statistically significant. As the number of sworn officers increase the number of total crime clearances increase. Moreover, percent community policing officers variable significantly predicts the change in the number of total clearances in Model 2. In other words as the percentage of community policing officers increase among all officers, total clearances also increase.

**Panel Models for Violent Crime Clearances**

In this part also, year 1997 is taken as the first wave in order to estimate the changes in violent crime clearances over time based on the changes in crime analysis and crime mapping adoption.

The first model is illustrated in the regression equation in Equation 14.

\[
Y_{\text{cleared violent crime 2003}} = \beta_0 + \beta_1 Y_{\text{cleared violent crime 1997}} + \beta_2 X_{\text{violent crimes 2003}} + \beta_3 X_{\text{crime analysis 2003}} + \beta_4 \Delta X_{\text{crime analysis}} + \beta_5 X_{\text{crime mapping 2003}} + \beta_6 \Delta X_{\text{crime mapping}} + \\
\beta_7 X_{\text{population density 2003}} + \beta_8 X_{\text{education 2003}} + \beta_9 X_{\text{urban percentage 2003}} + \beta_{10} X_{\text{percent male 2003}} + \\
\beta_{11} X_{\text{percent black 2003}} + \beta_{12} X_{\text{percent below poverty 2003}} + \beta_{13} X_{\text{percent renters 2003}} + \beta_{14} X_{\text{sworn 2003}} + \\
\beta_{15} X_{\text{AFIS use 2003}} + \beta_{16} X_{\text{agency functions 2003}} + \beta_{17} X_{\text{geographic assignment 2003}} + \\
\beta_{18} X_{\text{community policing officers 2003}} + \epsilon
\]

In this model, the dependent variable is the change in violent crime clearances from year 1997 to 2003. The main explanatory variables are crime analysis and crime mapping use in 2003 and changes in crime analysis and crime mapping use from 1997 to 2003. Referring back to the hypothesis statement, the expected sign of $\beta_3$, $\beta_4$, $\beta_5$, and $\beta_6$ are positive and the expected values of the coefficients under the alternative hypothesis are;

$$H_A; \beta_3>0, \beta_4>0, \beta_5>0 \text{ and } \beta_6>0$$

The second model is illustrated in the regression equation in Equation 15.

\[
Y_{\text{cleared violent crime 2000}} = \beta_0 + \beta_1 Y_{\text{cleared violent crime 1997}} + \beta_2 X_{\text{violent crimes 2000}} + \beta_3 X_{\text{crime analysis 2000}} + \beta_4 \Delta X_{\text{crime analysis}} + \beta_5 X_{\text{crime mapping 2000}} + \beta_6 \Delta X_{\text{crime mapping}} + \beta_7 X_{\text{population density 2000}} + \beta_8 X_{\text{education 2000}} + \beta_9 X_{\text{urban percentage 2000}} + \beta_{10} X_{\text{percent male 2000}} + \beta_{11} X_{\text{percent black 2000}} + \beta_{12} X_{\text{percent below poverty 2000}} + \beta_{13} X_{\text{percent renters 2000}} + \beta_{14} X_{\text{sworn 2000}} + \beta_{15} X_{\text{AFIS use 2000}} + \beta_{16} X_{\text{agency functions 2000}} + \beta_{17} X_{\text{geographic assignment 2000}} + \beta_{18} X_{\text{community policing officers 2000}} + \epsilon
\]

**Equation 15 Regression Formula for Estimating Violent Crime Clearances in 2000**

In this model, the dependent variable is the change in violent crime clearances from year 1997 to 2000. The main explanatory variables are crime analysis and crime mapping use in 2000 and changes in crime analysis and crime mapping use from 1997 to 2000. The expected sign of $\beta_3$, $\beta_4$, $\beta_5$, and $\beta_6$ are positive and the expected values of these coefficients under the alternative hypothesis are;

$$H_A; \beta_3>0, \beta_4>0, \beta_5>0 \text{ and } \beta_6>0$$

The third model is illustrated in the regression equation in Equation 16.
Equation 16 Regression Formula for Estimating Violent Crime Clearances in 1999

\[ Y_{\text{cleared violent crime } 1999} = \beta_0 + \beta_1 Y_{\text{cleared violent crime } 1997} + \beta_2 X_{\text{violent crimes } 1999} + \beta_3 X_{\text{crime analysis } 1999} + \beta_4 \Delta X_{\text{crime analysis}} + \beta_5 X_{\text{crime mapping } 1999} + \beta_6 \Delta X_{\text{crime mapping}} + \beta_7 X_{\text{population density } 1999} + \beta_8 X_{\text{education } 1999} + \beta_9 X_{\text{urban percentage } 1999} + \beta_{10} X_{\text{percent male } 1999} + \beta_{11} X_{\text{percent black } 1999} + \beta_{12} X_{\text{percent below poverty } 1999} + \beta_{13} X_{\text{percent renters } 1999} + \beta_{14} X_{\text{sworn } 1999} + \beta_{15} X_{\text{agency functions } 1999} + \beta_{16} X_{\text{geographic assignment } 1999} + \beta_{17} X_{\text{community policing officers } 1999} + \epsilon \]

In the last model, the dependent variable is the change in violent crime clearances from year 1997 to 1999. The main explanatory variables are crime analysis and crime mapping use in 1999 and changes in crime analysis and crime mapping use from 1997 to 1999. The expected sign of \( \beta_3, \beta_4, \beta_5, \) and \( \beta_6 \) are positive and the expected values of these coefficients under the alternative hypothesis are;

\[ H_A; \beta_3 > 0, \beta_4 > 0, \beta_5 > 0 \text{ and } \beta_6 > 0 \]

Since AFIS use was not asked in LEMAS 1999 survey, this department level control variable was not added in this last model.

The regression results of all three models are given in Table 13.

According to the F test results, all three models have joint significance in predicting the dependent variable. Besides, the goodness of fit statistics (R-squared) signifies that in all models at least 71% of the variation in the dependent variable is explained by the models.

As in the models that predict change in total crime clearances, in these models that predict change in violent crime clearances, crime mapping use is a significant predictor of the dependent variable. Crime mapping use has positive instantaneous effect on the change in violent crime clearances from 1997 to 2000 (Model 2) since the coefficients on this variable is significant at .05 alpha level. In other words, current use of crime mapping increases total crime clearances over time.
Table 14 Static-Score Panel Models for Violent Crime Clearances

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Coefficients</td>
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<td>Coefficients</td>
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<td>Crime Analysis Change</td>
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<td>-0.77</td>
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<tr>
<td></td>
<td>(0.96)</td>
<td>(1.11)</td>
<td>(0.99)</td>
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<td>Crime Mapping Change</td>
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<td>(0.8)</td>
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<td>(1.24)</td>
<td>(1.37)</td>
<td>(1.57)</td>
</tr>
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<td>Crime Mapping</td>
<td>-0.14</td>
<td>2.75**</td>
<td>1.75</td>
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<td></td>
<td>(0.81)</td>
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<td>(1.17)</td>
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<tr>
<td>Control Variables</td>
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<td></td>
</tr>
<tr>
<td>Total Clearance in 1997</td>
<td>0.41***</td>
<td>0.30***</td>
<td>0.17*</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.08)</td>
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<td>Total Crime</td>
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<td>(0.00)</td>
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<td></td>
<td>(0.06)</td>
<td>(0.08)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Percent Urban</td>
<td>-0.01</td>
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<td>0.08</td>
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<tr>
<td></td>
<td>(0.12)</td>
<td>(0.21)</td>
<td>(0.08)</td>
</tr>
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<td>Percent Male</td>
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</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.18)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Percent African American</td>
<td>-0.04</td>
<td>-0.07**</td>
<td>0.00</td>
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<td>(0.02)</td>
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<td>Percent Below Poverty</td>
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<td>Percent Renter</td>
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<td>(0.07)</td>
<td>(0.11)</td>
<td>(0.21)</td>
</tr>
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<td>Sworn Officers</td>
<td>1.19***</td>
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<td></td>
<td>(0.28)</td>
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<td>(0.27)</td>
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<td>(0.3)</td>
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<tr>
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<td>(0.25)</td>
<td>(0.30)</td>
<td>(0.30)</td>
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<tr>
<td>Constant</td>
<td>-9.86</td>
<td>-5.67</td>
<td>3.41</td>
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<tr>
<td></td>
<td>(16.53)</td>
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<td>(6.88)</td>
</tr>
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<td>N</td>
<td>214</td>
<td>215</td>
<td>215</td>
</tr>
<tr>
<td>F</td>
<td>107.69***</td>
<td>94.26***</td>
<td>36.04***</td>
</tr>
<tr>
<td>R²</td>
<td>0.82</td>
<td>0.71</td>
<td>0.74</td>
</tr>
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Significance levels based on a one-tailed test: *** p < .001, ** p < .01, * p < .05. Robust standard errors in parenthesis.
In this case, however, number of sworn personnel per 1,000 population is statistically significant only in the first model. That is, as the number of sworn personnel increased, there has been a significant increase in violent crime clearances between years 1997 and 1999.

As with the change in total crime clearances from 1997 to 2000 model, the percent community policing officers variable significantly predicts the change in the number of violent crime clearances from 1997 to 2000. In other words as the percentage of community policing officers increase among all officers, violent crime clearances also increase. This effect is not evident in models 1 and 3.

**Panel Models for Property Crime Clearances**

In this part also, year 1997 is taken as the first wave in order to estimate the changes in property crime clearances over time based on the changes in crime analysis and crime mapping adoption.

The first model is illustrated in the regression equation in Equation 17.

\[
Y_{\text{cleared property crime 2003}} = \beta_0 + \beta_1 Y_{\text{cleared property crime 1997}} + \beta_2 X_{\text{property crimes 2003}} + \beta_3 X_{\text{crime analysis 2003}} + \beta_4 \Delta X_{\text{crime analysis}} + \beta_5 X_{\text{crime mapping 2003}} + \beta_6 \Delta X_{\text{crime mapping}} + \beta_7 X_{\text{population density 2003}} + \beta_8 X_{\text{education 2003}} + \beta_9 X_{\text{urban percentage 2003}} + \beta_{10} X_{\text{percent male 2003}} + \beta_{11} X_{\text{percent black 2003}} + \beta_{12} X_{\text{percent below poverty 2003}} + \beta_{13} X_{\text{percent renters 2003}} + \beta_{14} X_{\text{sworn 2003}} + \beta_{15} X_{\text{AFIS use 2003}} + \beta_{16} X_{\text{agency functions 2003}} + \beta_{17} X_{\text{geographic assignment 2003}} + \beta_{18} X_{\text{community policing officers 2003}} + \varepsilon
\]

**Equation 17 Regression Formula for Estimating Property Crime Clearances in 2003**

In this model, the dependent variable is the change in property crime clearances from year 1997 to 2003. The main explanatory variables are crime analysis and crime mapping use in 2003 and changes in crime analysis and crime mapping use from 1997 to 2000.
2003. The expected sign of $\beta_3$, $\beta_4$, $\beta_5$, and $\beta_6$ are positive and the expected values of the coefficients under the alternative hypothesis are:

$$H_A; \beta_3>0, \beta_4>0, \beta_5>0 \text{ and } \beta_6>0$$

The second model is illustrated in the regression equation in Equation 18.

$$Y_{cleared \ property \ crime \ 2000} = \beta_0 + \beta_1 Y_{cleared \ property \ crime \ 1997} + \beta_2 X_{property \ crimes \ 2000} +$$  
$$\beta_3 X_{crime \ analysis \ 2000} + \beta_4 X_{crime \ analysis \ 2000} + \beta_5 X_{crime \ mapping \ 2000} + \beta_6 X_{crime \ mapping \ 2000} +$$  
$$\beta_7 X_{population \ density \ 2000} + \beta_8 X_{education \ 2000} + \beta_9 X_{urban \ percentage \ 2000} + \beta_{10} X_{percent \ male \ 2000} +$$  
$$\beta_{11} X_{percent \ black \ 2000} + \beta_{12} X_{percent \ below \ poverty \ 2000} + \beta_{13} X_{percent \ renters \ 2000} + \beta_{14} X_{sworn \ 2000} +$$  
$$\beta_{15} X_{AFIS \ use \ 2000} + \beta_{16} X_{agency \ functions \ 2000} + \beta_{17} X_{geographic \ assignment \ 2000} +$$  
$$\beta_{18} X_{community \ policing \ officers \ 2000} + \epsilon$$

**Equation 18 Regression Formula for Estimating Property Crime Clearances in 2000**

In this model, the dependent variable is the change in property crime clearances from year 1997 to 2000. The main explanatory variables are crime analysis and crime mapping use in 2000 and changes in crime analysis and crime mapping use from 1997 to 2000. The expected sign of $\beta_3$, $\beta_4$, $\beta_5$, and $\beta_6$ are positive and the expected values of the coefficients under the alternative hypothesis are:

$$H_A; \beta_3>0, \beta_4>0, \beta_5>0 \text{ and } \beta_6>0$$

The last model is illustrated in the regression equation in Equation 19.

$$Y_{cleared \ property \ crime \ 1999} = \beta_0 + \beta_1 Y_{cleared \ property \ crime \ 1997} + \beta_2 X_{property \ crimes \ 1999} +$$  
$$\beta_3 X_{crime \ analysis \ 1999} + \beta_4 X_{crime \ analysis \ 1999} + \beta_5 X_{crime \ mapping \ 1999} + \beta_6 X_{crime \ mapping \ 1999} +$$  
$$\beta_7 X_{population \ density \ 1999} + \beta_8 X_{education \ 1999} + \beta_9 X_{urban \ percentage \ 1999} + \beta_{10} X_{percent \ male \ 1999} +$$  
$$\beta_{11} X_{percent \ black \ 1999} + \beta_{12} X_{percent \ below \ poverty \ 1999} + \beta_{13} X_{percent \ renters \ 1999} + \beta_{14} X_{sworn \ 1999} +$$  
$$\beta_{15} X_{AFIS \ use \ 1999} + \beta_{16} X_{agency \ functions \ 1999} + \beta_{17} X_{geographic \ assignment \ 1999} + \beta_{18} X_{community \ policing \ officers \ 1999} + \epsilon$$

**Equation 19 Regression Formula for Estimating Property Crime Clearances in 1999**

In the last model, the dependent variable is the change in property crime clearances from year 1997 to 1999. The main explanatory variables are crime analysis and crime mapping use in 1999 and changes in crime analysis and crime mapping use.
from 1997 to 1999. The expected sign of $\beta_3$, $\beta_4$, $\beta_5$, and $\beta_6$ are positive and the expected values of the coefficients under the alternative hypothesis are:

$$H_A; \beta_3>0, \beta_4>0, \beta_5>0 \text{ and } \beta_6>0$$

Since AFIS use was not asked in LEMAS 1999 survey, this department level control variable was not added in this model.

The regression results of all three models are given in Table 15.

According to the F test results, all three models have joint significance in predicting the dependent variable. Besides, the goodness of fit statistics (R-squared) signifies that in all models at least 61% of the variation in the dependent variable is explained by the models.

As with the previous sections, in the models that predict change in property crime clearances, crime mapping use is a significant predictor of the dependent variable. Crime mapping use has positive instantaneous effect on the change in violent crime clearances from 1997 to 2003 (Model 3) since the coefficient on this variable is significant at .05 alpha level. In other words, current use of crime mapping increases total crime clearances over time.

In all three models, number of sworn officers per 1,000 population variable is statistically significant. As the number of sworn officers increase the number of property crime clearances increase. Moreover, percent community policing officers variable significantly predicts the change in the number of property clearances in Model 3. In other words as the percentage of community policing officers increase among all officers, property crime clearances also increase in the last wave (1997-2003).
### Table 15 Static-Score Panel Models for Property Crime Clearances

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficients</th>
<th>Coefficients</th>
<th>Coefficients</th>
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</thead>
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<tr>
<td>Crime Analysis Change</td>
<td>-0.22</td>
<td>0.23</td>
<td>-0.11</td>
</tr>
<tr>
<td></td>
<td>(0.7)</td>
<td>(0.69)</td>
<td>(0.72)</td>
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<td>Crime Mapping Change</td>
<td>0.15</td>
<td>-0.24</td>
<td>0.1</td>
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<tr>
<td></td>
<td>(0.72)</td>
<td>(0.47)</td>
<td>(0.5)</td>
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<tr>
<td>Crime Analysis</td>
<td>1.53</td>
<td>-0.17</td>
<td>-0.94</td>
</tr>
<tr>
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<td>(0.93)</td>
<td>(1.08)</td>
<td>(0.96)</td>
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<tr>
<td>Crime Mapping</td>
<td>-0.38</td>
<td>0.36</td>
<td>1.51*</td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
<td>(0.78)</td>
<td>(0.69)</td>
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<table>
<thead>
<tr>
<th>Control Variables</th>
<th>Coefficients</th>
<th>Coefficients</th>
<th>Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Clearance in 1997</td>
<td>0.38***</td>
<td>0.37***</td>
<td>0.39***</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Total Crime</td>
<td>0.07***</td>
<td>0.07**</td>
<td>0.07***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Population Density</td>
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<td>-0.01*</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.005)</td>
<td>(0.00)</td>
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<tr>
<td>Education</td>
<td>0.03</td>
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</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.06)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Percent Urban</td>
<td>0.16</td>
<td>0.17</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.1)</td>
<td>(0.14)</td>
<td>(0.05)</td>
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<tr>
<td>Percent Male</td>
<td>0.21</td>
<td>-0.12</td>
<td>-0.11</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.18)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Percent African American</td>
<td>-0.02</td>
<td>-0.03**</td>
<td>-0.01</td>
</tr>
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<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.05)</td>
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<tr>
<td>Percent Below Poverty</td>
<td>0.03</td>
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<td>(0.1)</td>
<td>(0.12)</td>
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<td>Percent Renter</td>
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<td>0.1</td>
</tr>
<tr>
<td></td>
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<td>(0.07)</td>
<td>(0.14)</td>
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<tr>
<td>Sworn Officers</td>
<td>0.8***</td>
<td>0.69**</td>
<td>0.86**</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.22)</td>
<td>(0.31)</td>
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<td>AFIS use</td>
<td>0.13</td>
<td>-0.01</td>
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<tr>
<td></td>
<td></td>
<td>(0.28)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Agency Functions Index</td>
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<td>-0.08</td>
<td>-0.4</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(0.25)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Geographic Patrol</td>
<td>0.15</td>
<td>-0.27</td>
<td>-0.04</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.26)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Community Policing</td>
<td>0.24</td>
<td>0.4</td>
<td>0.39*</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.23)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Constant</td>
<td>-25.82*</td>
<td>-6.98</td>
<td>1.32</td>
</tr>
<tr>
<td></td>
<td>(12.87)</td>
<td>(18.32)</td>
<td>(4.36)</td>
</tr>
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N: 214 215 215
F: 39.24*** 116.59*** 25.82***
R²: 0.63 0.61 0.67

Significance levels based on a one-tailed test: *** p < .001, ** p < .01, * p < .05.
Robust standard errors in parenthesis.
Conclusion

The cross-sectional data analysis results show that increased crime analysis capability of police department increases effectiveness in terms of higher total clearances and higher property crime clearances in certain time periods, but not across all time periods. Another important finding is that controlling for total population of the jurisdiction and the crime rates, police effectiveness in terms of higher total clearances and higher property crime clearances increases as number of sworn officers per 1,000 population increases. For increase in total clearances, AFIS use is also a significant factor.

Panel data analysis using static-score modeling provides partial evidence that use of crime mapping increases crime clearances over time.

For the panel data analysis, I used three waves and the effect of crime mapping use on change in total crime clearances and violent crime clearances is evident in the last two waves (1997 to 2000 and 1997 to 2003). The effect is significant for property crime clearances only in the last wave (1997 to 2000). This shows that the current adoption of crime mapping, controlling for the effect of change in adopting behavior (start, continue, quit), matters in solving crimes.

Also in most of the models, the number of sworn personnel and percentage of community policing personnel among all sworn personnel significantly affect clearances over time even when controlled for jurisdiction size and crime rates.
CHAPTER 6

CONCLUSION

Summary

This dissertation has examined the diffusion, effectiveness and applications of crime analysis and crime mapping technologies in three empirical chapters. While diffusion of crime mapping and its effect on decision-making were the main subject matter in the first two empirical chapters, use of crime analysis by the police was added along with crime mapping in the discussion and incorporated in the statistical analyses in the third empirical chapter.

Crime control strategies based on traditional pin mapping have long been used by the police; however, computerized crime mapping is a relatively a new technology. Despite the substantial expense for capital and human resource requirements this technology has diffused fairly rapidly to police departments. The first empirical chapter examined the diffusion of crime mapping technology and tested whether there is a spatial aspect to this diffusion. The results of the analyses have shown that there is a spatial aspect to this diffusion. Geographically closer departments are more likely to adopt crime mapping technologies.

The second empirical chapter examined whether the information obtained from crime mapping has an impact on managerial decision-making in police departments.
Specifically, the analysis in the chapter examined whether the probability of using information obtained from crime mapping for decision-making increases as the amount of information increases. The theoretical argument behind the analysis is that while some claim that more information is good in decision-making since it increases the ability of the decision maker to make rational decisions, others maintain that too much information is hard to assess and evaluate for the purposes of decision-making due to time restrictions and the analytical capabilities of the decision maker. The analyses yielded results supporting the latter argument. To a certain extent police departments are likely to use information obtained from crime mapping in resource allocation and redistricting decisions, however, when the amount of information increases too much the departments are less likely to base such critical decisions on information acquired from crime mapping.

The third empirical chapter studied the effect of crime mapping and crime analysis technologies on police effectiveness, measured in terms of increased crime clearances. The argument was that by enabling the police to be present at the right place at the right time by taking advantage of analysis of previous crime, crime analysis and crime mapping help increase police effectiveness as measured by increased crime clearances. Two different methodologies were used to test the hypotheses stated in the chapter: cross sectional regression analysis and static score panel data analysis. In essence, the results of the analyses suggest that departments that employ crime mapping have increase in crime clearance over time. Also departments that use extensive crime analysis applications increase their effectiveness in terms of higher total and property
crime clearances.

Discussion

While the earliest crime mapping adopter started using crime mapping in 1977, there have been few adopters for almost a decade until the end of 1980s. By the 1990s the number of crime mapping adopters increased almost exponentially until 1997, the last year we have data on crime adopters based on the CCMLE survey. Considering the pattern proposed by innovation diffusion literature, the number of adopters must be increasing until it stabilizes and plateaus. The pattern becomes more obvious when supplementary information is added to the information as to adoption in CCMLE data. Indeed, when the number of crime mapping adopters from LEMAS data for the year 2000 and 2003 are added to the scatter plot data in Figure 2, the sigmoid curve pattern is evident as the number of adopters start to plateau by 2003.

Based on the analyses about the effect of crime analysis and crime mapping use on police effectiveness, I have found partial evidence to conclude that crime analysis and crime mapping use increase police effectiveness in terms of increased crime clearances. In the cross sectional analyses, I have used multiple indicators of crime mapping and crime analysis use as explanatory variables and not all of them were significantly associated with the dependent variables. Also, in the panel data analyses both change in use and instant use of crime mapping and crime analysis were included in the analyses, yet hardly any of the variables were significant in predicting the change in clearance rates over time.
Thus, this study concludes that crime mapping and crime analysis has little direct impact on police effectiveness in terms of increased crime clearances.

Policy Implications

Decision-Making

According to Manning (2003) if the usability of information technologies is not well calculated, purchasing, updating and/or upgrading new technologies may result in a critical mass disorder and organizational chaos, where information collection is merely a burden without a specific purpose and systematic organization. Considering the amount of information some police departments process just based on crime mapping, the need for a systematic information collection procedure and specific purpose become clearer. Taking the results of the analyses in the third chapter into account the need for a decision-making model for police managers that would enhance swift and accurate decision-making of the police manager is obvious. Here a brief suggestion for such a model will be made analogous to the ideas put forward by Buchanan and Tullock’s (1999) in their discussion of optimum decision-making in collective action. Buchanan and Tullock (1999) mainly suggest that individuals strive to increase their utility and decrease the costs while making decisions.

Even though their ideas about decision-making are economics oriented and derives from a perspective that compares and contrasts private and collective actions, there are some implications for organizational decision-making and information
processing. In their model of decision-making, if an individual makes decisions by
him/herself and acts independently and privately, the costs for realizing the goals of the
decision will be high but the decision-making costs will be none. However if the
individual decides to act interdependently and collectively and involves others in his/her
decision, the costs for realizing the goals of the decision may be low as it will be shared
collectively. However, there will be the cost of acquiring unanimity and cooperation and
full agreement of all parties involved in the collective action. In any decision-making
situation, in order to optimize the situation and keep the costs low there must be an
adequate number of people to take action collectively and share the costs and decide as
swiftly and economically as possible.

Likewise, in decision-making in police organizations, if the police manager
decides solely upon intuition without consulting external information, the decision-
making will be swifter but the costs associated with making a decision without
considering relevant information will be high. Here, the costs will be high but the time
required to take action will be significantly shorter as the decision-making process does
not involve any extraordinary effort for processing information. The costs associated with
irrelevant decisions will diminish as the decision maker takes relevant information into
account.

If the manager tries to take all the information available into account whether
relevant or not, the decision-making time will increase considerably, which is not a
favorable attribute in police decision-making. Thus, the information based decision-
making model argues that the manager must have enough and relevant information in
order to optimize the process of decision-making in shorter periods with as much relevant information as possible.

In that sense, the quality of information available to decision makers is crucial since they use available information when they are making decisions. Not all information, however, is relevant to the decision being considered or is refined enough for a to-the-point decision. Police departments generate too much information and police managers are required to make decisions about many issues. In order for the optimum decision, which is both accurate and swift, to be made, the police manager needs refined information that is relevant to the decisions and that is concise enough to allow for swift strategic decision-making. Such information can be obtained through strategic and directed analysis of information.

**Diffusion of Innovations**

Although the spatial aspect of the diffusion of crime mapping technology was examined in this study, the same theoretical and methodological framework can also be applied to other criminal justice related technologies and processes. Unlike many centralized countries that have a single, centralized and national police department, the United States has thousands of police departments and other law enforcement agencies in various sizes. It is, thus, very important to recognize how crime fighting technologies spread across those agencies so that new and recognized technologies can be introduced to all departments using the same channels.
This dissertation has established that there is a contagious effect to diffusion of crime mapping across police departments in the U.S. This finding suggests that geographical proximity matters in adopting innovations. Determining geographical pioneers and the most influential opinion leaders with respect to innovation diffusion will help introduce and spread new technologies. As opposed to spreading reports and brochures to police departments explaining the strengths of a new innovation, a suggestion from a peer, who has implemented the innovation, would be much more effective. As Rogers and Scott (1997, p. 6) put it “most individuals evaluate an innovation, not on the basis of scientific research by experts, but through the subjective evaluations of near-peers who have adopted the innovation.” Therefore by encouraging the early adopters to be more visible to their neighboring departments, those that do not consider adoption or consider adoption at a later time can be mobilized to adopt new technologies.

Limitations of the Study

Measurement Issues

The only indicator of police effectiveness used in this study is clearances by arrest from UCR data. Although it might be argued that crime rates are an important measure of police output, crime rates as measured in UCR was not used in the analyses because of several reasons. The first problem is that crime rates in UCR are “crimes known to the
police” as measured by criminal “events either reported to or observed by the police” (Inciardi, 1978, p. 4) not actual crime rates.

The second problem with crime rates as a measure of effectiveness, for the purposes of the theoretical relationships established in this dissertation, is that it is uncertain whether lower crime rates indicate efficiency (i.e. crime mapping technology produces actual decreases in crime) or whether higher rates of crimes reported to police indicate greater efficiency since this may be tapping greater cooperation by citizens with the police since they report more crime.

As a third problem, it is also not clear whether lower crime rates indicate efficiency in terms of crime mapping technology preventing more crime from occurring or whether higher rates of crimes indicate efficiency as a result of crime mapping tools enabling police to be at the right place at the right time and thus observe more crime.

Therefore, number of clearances by arrest per population is considered less ambiguous measure of efficiency and was used as the only police effectiveness indicator in this research.

**Generalizability**

Since the unit of analysis in the data sets used in this dissertation is law enforcement (alternatively referred to as police departments in the study) institutions at local and county level, the findings of the empirical analyses have national level generalizability in the U.S. U.S. has a rather unique governmental structure and there are
thousands of police departments in the country. This variation allows researchers to study various topics such as the ones studied in this dissertation.

The diffusion of crime mapping in countries with national and/or highly centralized policing might be very different as the adoption decision will be made by the central authority and the only difference in diffusion of the technology would be not in terms of adoption but in terms of level of adoption based on local resources. Also, one should take care in applying findings of the innovation diffusion research in this dissertation to other types of institutions. Last but not least, since the innovation that is studied in Chapter 3 is crime mapping, readers should cautiously evaluate the findings as other kinds of policing innovations might spread in different manners.

**Contributions of the Study**

Police departments invest huge amounts of money in crime analysis and crime mapping technologies with hopes that their effectiveness in fighting crime will increase. Naturally, police managers, their personnel, local governments that provide budget to the police department, and most importantly the public deserve to know whether this huge investment is cost-effective and providing what it promises to provide. This study shows that use of crime analysis and crime mapping have little contribution to police effectiveness in terms of crime solving capabilities.

The methodology used in this study can be applied to other police innovation diffusion processes and the findings can shed light to how new technologies diffuse among police departments in the U.S. Since this research has established that geographic
proximity matters in adoption of crime mapping, change agents can use this information in promoting new technologies. Using this information, federal agencies such as the National Institute of Justice and U.S. Department of Justice can help spread programs and innovations that they deem to be effective in policing by identifying local or regional leaders that can influence the decisions of neighboring departments in what to or not to adopt.

In terms of the contribution of this research based on its findings as to the use of information obtained from crime mapping, this dissertation touches upon a very crucial issue; the quality and parsimony of information based on crime analysis. Police officers, police managers and especially crime analysts should know that more information is good to the extent that it is usable in making decisions. Since at the heart of acquisition of information from crime analysis lies use of this information in making necessary changes to increase the effectiveness of the department. This study established that police departments that produce extensive amounts of information are less likely to use information in strategic decision-making and thus information is useful as long as it is to-the-point, relative and parsimoniously articulated.

Apart from the above mentioned specific contribution of this research, there are general contributions as well. This dissertation adds to the literature of four different fields of study; police effectiveness, criminology, innovation-diffusion and decision-making. Especially, the findings in Chapter 5 empirically contribute to the theoretical arguments of some main criminological theories. Also a rarely studied and recently overlooked aspect of innovation-diffusion is investigated in this dissertation; spatial
diffusion. With globalization and advances in communication technology geographical proximity is considered to have lost its impact on diffusion of innovations (Fichman, 2001; Habito, 2002; Zebich-Knos, 2006). However, this research has clearly shown that geographical proximity still matters.

Furthermore, the findings of Chapter 4 significantly add to the vast literature on decision-making. Especially, this study adds tremendously to the discussion on and contradictory views about the rationality of the decision maker. As discussed extensively in Chapter 4, decision makers are rational to the extent that they have all the information concerning the subject matter. However, all available information does not necessarily add to the rationality of the decision maker since information is useful when it is concise and relevant. Therefore, when there is too much information there is no information based rational decision-making unless relevant portion of the information can be extracted from the load of available information.

**Future Research Suggestions**

The only available nationwide data (Use of Computerized Crime Mapping by Law Enforcement in the U.S.) on crime mapping use and applications in police departments is based on a survey that was conducted in 1997-1998 and the data is available only with restricted use while similar data with similar strategic information (Law Enforcement Management and Administrative Statistics Series) are available without restriction for all researchers. Thus there is a need for a new survey on crime mapping activities and implementation of police departments.
The new survey should not only include sections with questions on various crime mapping/crime analysis activities (frequency and type of techniques used) and resources (number of personnel, dedicated unit, hardware and software used) but also detailed sections on budget allocated to technology by the police department and decision-making. This way, the researchers will be able to study effectiveness, efficiency, decision-making, policy-making and administrational aspects of technology use in police departments. Besides the data set created based on the new survey should be made available for empirical research as swiftly as possible.
REFERENCES


APPENDIX 1

USE OF COMPUTERIZED CRIME MAPPING DATA COLLECTION INSTRUMENT
Crime Mapping Survey

Data supplied by

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<th>Name</th>
<th>Title</th>
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<table>
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<th>State</th>
<th>ZIP Code</th>
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<table>
<thead>
<tr>
<th>Enter your 9 digit NCIC-ORI number</th>
<th>Telephone (area code, number, extension)</th>
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</thead>
</table>

RETURN TO (postage paid envelope enclosed)

OFFICE OF RESEARCH AND EVALUATION
NATIONAL INSTITUTE OF JUSTICE
810 7th Street, NW
Washington, DC 20531

FROM THE DIRECTOR
NATIONAL INSTITUTE OF JUSTICE

As Director of the National Institute of Justice, the research arm of the Department of Justice, I am writing to request your help in completing a national survey that will advise our newly established Crime Mapping Research Center (CMRC). The Center’s work includes the development and implementation of a crime mapping training program for crime analysts and other criminal justice researchers. Thus, this survey is designed to determine the extent to which police departments, specifically crime analysts, are using computerized crime mapping. If you feel you are not the correct person within your department to answer this survey, please forward this survey to the person who can best respond to the survey questions.

Your agency and other agencies in the scientifically selected sample will represent the characteristics and work of all law enforcement agencies in the United States. Please be advised that your responses to this survey are strictly confidential; your name will not be associated with your individual responses, and survey results will be reported in the aggregate, not department by department. If you are uncomfortable answering a particular survey question, please feel free to skip the question. So that we can complete data collection and publish the survey results as soon as possible, please complete this questionnaire by October 31, 1997 and return it in the enclosed envelope. If you need assistance in completing the questionnaire, call Cyndy Nahabedian at (202) 514-5981.

Public reporting burden for this collection of information is estimated to average 33 minutes per survey, including the time for reviewing instructions, gathering the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspects of this collection of information, including suggestions for reducing this burden, to the Director, National Institute of Justice, 810 7th Street, NW, Washington, DC 20531; and to the Office of Management and Budget, OMB number 1121-0223, Washington, DC 20530.

Thank you for your cooperation and participation in this voluntary survey. Your responses will be extremely useful in helping us better serve the criminal justice community in the area of crime mapping.

Sincerely,

Jeremy Travis
Director
National Institute of Justice

Would you be interested in receiving the Executive Summary of the results of this survey? □ Yes □ No

Would you mind if a Department of Justice staff person contacted you with follow-up questions to your responses? □ Yes □ No
SECTION I: DESCRIPTIVE INFORMATION
Which category below best describes your agency type? *Mark (X) only one box.*

1. General purpose municipal police department
2. General purpose county police department
3. State police department
4. Sheriff’s department
5. Special police department (e.g. campus police, transit police, airport police, housing police, alcoholic beverage control, natural resources police, park police, etc.)

What is the population size of the community the agency services?

Please provide the following information:

<table>
<thead>
<tr>
<th>Organizational Title/Name</th>
<th>No. of Sworn Personnel</th>
<th>No. of Non-Sworn Personnel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agency/Department (ex. NYPD)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Your Bureau/Division (ex. Patrol Division)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Your Section/Unit (ex. Crime Analysis Unit)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For which of the following crimes does the department keep incident based computer records?
*Mark (X) all that apply.*

1. Robbery
2. Homicide
3. Rape
4. Aggravated Assault
5. Common Assault
6. Disorderly conduct
7. Burglary
8. Larceny/theft
9. Motor vehicle theft
10. Arson
11. Weapons Violations
12. Gangs
13. Drug offenses
14. Domestic Violence
15. Traffic offenses
16. Forgery/Fraud
17. Vandalism/Destruction of Property
18. Firearm discharges
19. Gambling
20. Kidnapping
21. Prostitution
22. Other sex offenses
23. DUI/DWI
24. None

SECTION II: OPERATIONS

1. Which types of crime analysis does your section or unit currently perform? *Mark (X) all that apply.*

1. Point pattern analysis
2. Pin maps
3. Trend analyses
4. UCR Reports
5. Case Studies
6. Incident Recaps
7. Statistical Reports
8. Linkage analysis
9. Pattern detection
10. Strategic analysis/Situational analysis

2. Does your department currently do any computerized crime mapping?
   1. Yes
   2. No - *SKIP to Section VII, Question 37*

3a. If you answered yes to question 2, who actually performs the computerized crime mapping queries? *Mark (X) all that apply.*

1. Crime analysis staff
2. Patrol officers
3. Investigations staff
4. Dispatch
5. Other (Specify)

3b. What percent of staff in each of the above marked categories actually perform computerized crime mapping queries?

<table>
<thead>
<tr>
<th>Crime Analysis Staff</th>
<th>Patrol Officers</th>
<th>Investigations Staff</th>
<th>Dispatch</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>%</td>
<td>%</td>
<td>%</td>
<td>%</td>
<td>%</td>
</tr>
</tbody>
</table>
### SECTION III: EQUIPMENT

#### 7a. Does your department use a commercially available software package for mapping?

<table>
<thead>
<tr>
<th></th>
<th>1 Yes</th>
<th>2 No - SKIP to question 8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### b. If your response to question 7a was yes, which software package(s) do you use? *Mark (X) all that apply.*

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ArcInfo</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>ArcView</td>
<td>7</td>
</tr>
<tr>
<td>3</td>
<td>Atlas GIS</td>
<td>8</td>
</tr>
<tr>
<td>4</td>
<td>IDRISI</td>
<td>9</td>
</tr>
<tr>
<td>5</td>
<td>Intergraph</td>
<td>10</td>
</tr>
</tbody>
</table>

#### c. What version of the above software does your unit predominantly use in crime mapping (e.g. ArcView, Version 2.1)?

#### 8. Has your department customized a commercially available mapping application or developed a custom mapping program specifically for internal use?

<table>
<thead>
<tr>
<th></th>
<th>1 Yes</th>
<th>2 No</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 9a. Please indicate which additional type(s) of software your department uses. *Mark (X) all that apply.*

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Database management</td>
<td>5</td>
<td>E-mail</td>
</tr>
<tr>
<td>2</td>
<td>Statistical</td>
<td>6</td>
<td>Network management</td>
</tr>
<tr>
<td>3</td>
<td>Spreadsheets</td>
<td>7</td>
<td>Project management</td>
</tr>
<tr>
<td>4</td>
<td>Word processing</td>
<td>8</td>
<td>Desktop Publishing</td>
</tr>
<tr>
<td>9</td>
<td>CAD/CAM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Multimedia applications</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Other (Specify)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### b. If your department uses database management software, please indicate which program(s) it uses. *Mark (X) all that apply.*

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Oracle</td>
<td>5</td>
<td>Paradox</td>
</tr>
<tr>
<td>2</td>
<td>Foxpro/Foxbase</td>
<td>6</td>
<td>Sybase</td>
</tr>
<tr>
<td>3</td>
<td>Dbase</td>
<td>7</td>
<td>Other (Specify)</td>
</tr>
<tr>
<td>4</td>
<td>Microsoft Access</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
10. How many computers does your department use for crime mapping?

11a. Which of the following are used by your department for crime mapping?

Mark (X) all that apply.

1☐ Mainframe
2☐ PC/Desktop
3☐ Network

4☐ Laptop
5☐ Other (Specify) __________________________

b. Which operating systems are being used on your department’s computer setup?

Mark (X) all that apply.

1☐ Windows NT
2☐ Windows 3.X
3☐ Windows 95
4☐ UNIX
5☐ Novell
6☐ OS/2
7☐ MacIntosh
8☐ DOS
9☐ Other (Specify) __________________________

12. Does your department use the Internet (Email or the World Wide Web)?

1☐ Yes 2☐ No - SKIP to question 14a

13. If you answered yes to question 12, how likely is it that you, or your department, would subscribe to an email or electronic bulletin board about computerized crime mapping? (Circle appropriate number, where 1 = Not very likely and 5 = Very likely).

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not very likely</td>
<td>Very likely</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

14a. Does the department use a global positioning system (GPS) to assist in any part of its operation?

1☐ Yes 2☐ No - SKIP to question 15

b. If you answered yes to question 14a, how does the department use a GPS to assist in its operations? Mark (X) all that apply.

1☐ Officer/patrol car location system
2☐ 911 call-for-service location identification
3☐ Street correction/validation
4☐ Tracking offender movement
5☐ Other (Specify) __________________________

SECTION IV: ANALYSIS

15. What type of data does your department geocode and map? Mark (X) all that apply.

1☐ Calls for service (CAD)
2☐ Offense data
3☐ Adult offenders
4☐ Juvenile offenders
5☐ Probationers
6☐ Prison releases
7☐ Vehicle recoveries
8☐ Property recoveries (other)
9☐ Field intelligence reports
10☐ Gang related crime incidents (gang motivated)
11☐ Gang related crime incidents (gang membership involvement)
12☐ Other (Specify) __________________________

16. Which types of crimes does your department map? Mark (X) all that apply.

1☐ Robbery
2☐ Homicide
3☐ Rape
4☐ Agg. Assault
5☐ Common Assault
6☐ Disorderly conduct
7☐ Burglary
8☐ Larceny/theft
9☐ Motor vehicle theft
10☐ Arson
11☐ Weapons Violations
12☐ Gangs
13☐ Drug offenses
14☐ Domestic Violence
15☐ Traffic offenses
16☐ Forgery/Fraud
17☐ Firearm Discharges
18☐ DUI/DWI
19☐ Gambling
20☐ Kidnapping
21☐ Prostitution
22☐ Other sex offenses
23☐ Vandalism/Destruction of Property

17. What types of computerized crime mapping analyses does the department perform?

Mark (X) all that apply.

1☐ Automated pin maps
2☐ Trend analyses
3☐ Temporal analyses
4☐ Offender movement
5☐ Pattern analyses
6☐ Situational Analysis
7☐ Other (Specify) __________________________
18. How often does the department conduct crime mapping analyses? *Mark (X) all that apply.*

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>1</td>
</tr>
<tr>
<td>Monthly</td>
<td>4</td>
</tr>
<tr>
<td>Weekly</td>
<td>2</td>
</tr>
<tr>
<td>As needed</td>
<td>5</td>
</tr>
<tr>
<td>Bi-weekly</td>
<td>3</td>
</tr>
<tr>
<td>Other (Specify)</td>
<td>6</td>
</tr>
</tbody>
</table>

19a. Does the department conduct crime cluster or hot spot analyses?  

1 □ Yes  
2 □ No - *SKIP to question 20*

b. If you answered yes to question 19a, please indicate which crime cluster or hot spot analysis methods are used by the department. *Mark (X) all that apply.*

<table>
<thead>
<tr>
<th>Method</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual identification of hot spots</td>
<td>1</td>
</tr>
<tr>
<td>Computer program that identifies hot spots (e.g. STAC) (Specify)</td>
<td>2</td>
</tr>
<tr>
<td>Other (Specify)</td>
<td>3</td>
</tr>
</tbody>
</table>

20. How does the department use the results produced by crime mapping analyses? *Mark (X) all that apply.*

<table>
<thead>
<tr>
<th>Use of Results</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inform patrol officers and investigators</td>
<td>1</td>
</tr>
<tr>
<td>Apply or evaluate specific interventions</td>
<td>2</td>
</tr>
<tr>
<td>Identify locations with repeat calls-for-service</td>
<td>3</td>
</tr>
<tr>
<td>Assist in resource allocation decisions</td>
<td>4</td>
</tr>
<tr>
<td>Assist dispatchers</td>
<td>5</td>
</tr>
<tr>
<td>Inform the community</td>
<td>6</td>
</tr>
<tr>
<td>Redistricting (e.g. beats, reporting areas)</td>
<td>7</td>
</tr>
<tr>
<td>Other administrative decisions</td>
<td>8</td>
</tr>
<tr>
<td>Other (Specify)</td>
<td>9</td>
</tr>
</tbody>
</table>

SECTION V: MAPFILES

21. What is the source of the street map your department uses for crime mapping? *Mark (X) all that apply.*

<table>
<thead>
<tr>
<th>Source</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commercial vendor (Specify)</td>
<td>1</td>
</tr>
<tr>
<td>Government agency (Specify)</td>
<td>2</td>
</tr>
<tr>
<td>Develop mapfiles in-house</td>
<td>3</td>
</tr>
<tr>
<td>Other (Specify)</td>
<td>4</td>
</tr>
</tbody>
</table>

22. Which of the following best describes the reference files that you use for geocoding and crime mapping? *Mark (X) all that apply.*

<table>
<thead>
<tr>
<th>Reference Files</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Street centerlines</td>
<td>1</td>
</tr>
<tr>
<td>Parcel database</td>
<td>2</td>
</tr>
<tr>
<td>Other (Specify)</td>
<td>3</td>
</tr>
</tbody>
</table>

23. Have street maps been edited for accuracy and detail? *Mark (X) all that apply.*

<table>
<thead>
<tr>
<th>Maps Edited</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maps are not edited</td>
<td>1</td>
</tr>
<tr>
<td>Address verification function in dispatch system</td>
<td>2</td>
</tr>
<tr>
<td>Address verification function in records management system</td>
<td>3</td>
</tr>
<tr>
<td>Extensive edits to street maps have been made</td>
<td>4</td>
</tr>
<tr>
<td>Other (Specify)</td>
<td>5</td>
</tr>
</tbody>
</table>

24. How often are your street maps updated? *Mark (X) only one box.*

<table>
<thead>
<tr>
<th>Update Frequency</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly</td>
<td>1</td>
</tr>
<tr>
<td>Quarterly</td>
<td>2</td>
</tr>
<tr>
<td>Yearly</td>
<td>3</td>
</tr>
<tr>
<td>Maps are not updated</td>
<td>4</td>
</tr>
<tr>
<td>Other (Specify)</td>
<td>5</td>
</tr>
</tbody>
</table>
### SECTION VI: ADMINISTRATION

25. Which level(s) in the department and/or jurisdiction receive and respond to requests for computerized crime maps? Mark (X) all that apply.

- 1. Command officers
- 2. Patrol officers
- 3. Chief’s office
- 4. Investigation unit
- 5. Special task forces
- 6. Mayor
- 7. City council
- 8. Other city officials
- 9. Commissioner
- 10. Community groups
- 11. Other (Specify) ____________

26a. Does the department keep an archive of geocoded data?  
1. Yes  
2. No - SKIP to question 27a

b. If you answered yes to question 26a, for which years does the department have geocoded data?  
19 ____________ to 19 ____________

c. If you answered yes to question 26a, for how long does the department archive the geocoded data? If there is an exact amount of time, please specify.  
[Months or Years or Days]

27a. Does the department use other external data sources in conjunction with its geocoded crime data?  
1. Yes  
2. No - SKIP to question 28a

b. If you answered yes to question 27a, please indicate which external data sources are used. Mark (X) all that apply.

- 1. City planning data
- 2. Census data
- 3. Housing authority data
- 4. Parks information
- 5. Utilities information
- 6. Property assessment data
- 7. Student population data (Dept of Education)
- 8. Business listings
- 9. Other (Specify) ____________

28a. Does your unit or division work with other departments or divisions internal to the police agency in coordinated computerized crime mapping analyses?  
1. Yes  
2. No - SKIP to question 29a

b. If you answered yes to question 28a, please list by name the 3 other departments or divisions with whom you coordinate most ____________ ____________ ____________

29a. Does your department or division work with other police departments to conduct cross-jurisdictional computerized crime mapping analyses?  
1. Yes  
2. No - SKIP to question 30

b. If you answered yes to question 29a, with how many other departments does your department do crime mapping work?  
____________________________

c. If you answered yes to question 29a, through what mechanism does the department conduct cross-jurisdictional computerized crime mapping analyses? Mark (X) all that apply.

- 1. Specialized task force
- 2. Interagency consortium
- 3. Other (Specify) ____________
30. If the Department of Justice offered training in crime mapping techniques and analyses, which format would be most useful to your department? *Mark (X) only one box.*

1. Written text
2. Face to face onsite workshop
3. Video training tapes
4. Interactive sessions on the Internet
5. Two-way interactive audio and video
6. Other *(Specify)* 

31. If face to face training workshops were made available, of which arrangement would you most likely take advantage? *Mark (X) only one box.*

1. Training provided at the CMRC in Washington, DC
2. Specially convened training session in your state or region
3. National conference

32. Which of the following statements best characterizes your department’s interest in computer training for crime mapping? *Mark (X) only one box.*

1. We would send key employees if costs were reasonable
2. We would send key employees if no costs were involved
3. We are interested but have no budget for training
4. We are interested in information only at this point
5. We are not interested

33. Please rate the likelihood that your department would send employees to a conference on computer mapping techniques and analyses (Circle appropriate number, where 1 = Not very likely and 5 = Very likely).

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not very likely</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Very likely</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

34. Rate each of the following factors according to the extent to which they have a negative impact on your department’s ability to use crime mapping effectively (Circle the appropriate number, where 1 = No problem and 5 = Serious problem).

<table>
<thead>
<tr>
<th>Limited computer resources</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Limited financial resources</td>
<td>No problem</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Limited time</td>
<td>No problem</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Limited training opportunities</td>
<td>No problem</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Limited working knowledge of how mapping is used in the field</td>
<td>No problem</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Limited interest from administration</td>
<td>No problem</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Limited interest from support staff</td>
<td>No problem</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Difficulties with computer software</td>
<td>No problem</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Other <em>(Specify)</em></td>
<td>No problem</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>No problem</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>
35. Which funding sources has your department used to support each of the following costs for crime mapping? *Mark (X) all that apply.*

<table>
<thead>
<tr>
<th>COPS</th>
<th>BJA Law Enforcement Block Grant</th>
<th>Byrne Block Grant</th>
<th>Partnership with State or Local Agency</th>
<th>Partnership with University</th>
<th>Private Foundation</th>
<th>Dept Annual Budget</th>
<th>Asset Forfeiture</th>
<th>Other</th>
<th>None</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hardware</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Software</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Training</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technical Assistance</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

36. Rate each of the following statements about your department’s support of crime mapping (Circle the appropriate number, where 1 = Not accurate and 5 = Very accurate).

- **Leadership financially supports crime mapping efforts**: 1 2 3 4 5 Not accurate Very accurate
- **It is well accepted within the department that mapping is a valuable tool**: 1 2 3 4 5 Not accurate Very accurate
- **Mapping directives come from the top**: 1 2 3 4 5 Not accurate Very accurate

Thank you for completing this survey. Your feedback is very important to us. Please return the completed survey in the envelope provided.

Place additional comments here.

*If you require additional room, please continue comments on the back of the survey instrument.*

Thank you.
SECTION VII: SURVEY CONTINUATION FOR DEPARTMENTS NOT USING GIS

37. Has your department made plans to purchase equipment or software for computerized crime mapping within the next year? 1 □ Yes 2 □ No

38. Rate each of the following factors according to the extent to which they have a negative impact on your department’s ability to initiate crime mapping (Circle appropriate number, where 1 = No problem and 5 = Serious problem).

<table>
<thead>
<tr>
<th>Limited computer resources</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>Serious problem</th>
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<tbody>
<tr>
<td>Limited financial resources</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>Serious problem</td>
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<td>Limited time</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>Serious problem</td>
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<td>Limited training opportunities</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>Serious problem</td>
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<tr>
<td>Limited working knowledge of how mapping is used in the field</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>Serious problem</td>
</tr>
<tr>
<td>Limited interest from administration</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>Serious problem</td>
</tr>
<tr>
<td>Limited interest from support staff</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>Serious problem</td>
</tr>
<tr>
<td>Difficulties with computer software</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>Serious problem</td>
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<tr>
<td>Other (Specify)</td>
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39a. Does the department maintain computerized crime data? 1 □ Yes 2 □ No

b. Please indicate the type(s) of computer software used by the department. Mark (X) all that apply.

1 □ Database management 5 □ E-mail 9 □ CAD/CAM
2 □ Statistical 6 □ Network management 10 □ Multimedia applications
3 □ Spreadsheets 7 □ Project management 11 □ Other (Specify) ___________
4 □ Word processing 8 □ Desktop Publishing 12 □ None of the above

c. If your department uses database management software, please indicate which program(s) you use. Mark (X) all that apply.

1 □ Oracle 5 □ Paradox
2 □ Foxpro/Foxbase 6 □ Sybase
3 □ Dbase 7 □ Other (Specify) ___________
4 □ Microsoft Access

40. Would crime mapping software that requires minimal training be useful to your department? (Circle appropriate number, where 1 = Not very useful and 5 = Very useful).

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<tr>
<td>Not very useful</td>
<td>Very useful</td>
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41. If the Department of Justice offered training in crime mapping techniques and analyses, which format would be most useful to your department? *Mark (X) only one box.*

1. ☐ Written text  4. ☐ Interactive sessions on the Internet
2. ☐ Face to face onsite workshop  5. ☐ Two-way interactive audio and video
3. ☐ Video training tapes  6. ☐ Other *(Specify)*

42. If face to face training workshops were made available, of which arrangement would you most likely take advantage? *Mark (X) only one box.*

1. ☐ Training provided at the CMRC in Washington, DC
2. ☐ Specially convened training session in your state or region
3. ☐ National conference

43. Which of the following statements best characterizes your department’s interest in computer training for crime mapping? *Mark (X) only one box.*

1. ☐ We would send key employees if costs were minimal
2. ☐ We would send key employees if no costs were involved
3. ☐ We are interested but have no budget for training
4. ☐ We are interested in information only at this point
5. ☐ We are not interested

44. Please rate the likelihood that your department would send employees to a conference on computer mapping techniques and analyses (Circle appropriate number, where 1 = Not very likely and 5 = Very likely).

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<tr>
<td>Not very likely</td>
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<td>Very likely</td>
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Thank you for completing this survey. Your feedback is very important to us. Please return the completed survey in the envelope provided.

Place additional comments here.
APPENDIX 2

DATA MERGING PROCESS
The merging of the data sets was achieved through several stages as explained below;

- First, data sets were downloaded from the ICPSR web page.
- UCR data sets have been cleared. Monthly crime and clearance data have been combined into annual crime and clearance rates.
- Names of key variables have been harmonized across UCR data sets.
- Unique key variables that identify each department have been added to each UCR data set from the Crosswalk data.
- Unique key variables that identify each department have been added to each LEMAS data set from the Crosswalk data. At this point decimal differences were observed in unique identifiers across the Crosswalk data and 1997 and 1990 LEMAS data sets. Differences were manually eliminated and data sets were successfully merged.
- The unique identifier in the restricted crime mapping data set (CCMLE) that was provided by NACJD was missing on almost 260 cases and of those approximately 50 departments stated that they employed crime mapping in their daily operations. In that sense a second attempt was made in order to obtain more identifiers such as the department name, city name, county name and the state name. Except for the county name, the requested identifiers were provided by NACJD. Based on those new criteria I matched each case that was missing the ORI code in the Crosswalk data set and filled in values of the unique identifier. As a result, 245 of the missing identifiers were restored.
- After restoring missing cases, the researcher attempted to merge the crime mapping data with UCR crime data for the year 1997. After merging, 203 cases were
missing values on the crime variables. Those 203 cases were examined one by one and it was observed that some departments that responded to the crime mapping survey did not respond to UCR. It was also observed that while the state, city and department names matched for some cases, ironically the unique identifiers did not match. Further investigation revealed that there are two types of ORI codes that were used to identify police departments in different data sets. ORI code is a unique identifier that starts with two letter state code and a unique identifying number for each agency within that state. However the numeric code that comes after the state code is five digits in some data sets and 7 digits in others. In some cases the number “zero” (0) that comes after the state code was coded as the letter “O” causing mismatches between ORI codes. For instance the ORI code for Minneapolis Police Department is coded as MNO2711 in CCMLE data set while the code is MN02711 in UCR 1997 data set.

I encountered similar problems while merging LEMAS 1997 data set into CCMLE data set. While ORI code is the common key identifier in CCMLE and UCR data sets, the key identifier in LEMAS data set is 16 digits of unique agency identification numbers. Although the crosswalk data set provides both ORI code and the corresponding agency identification number, there are over 2500 agencies that have no agency identification number. Also not all agencies that have responded to the CCMLE survey responded to the LEMAS survey.

The merging process with the CENSUS data was made possible with the key identifiers that are present in both data sets. The only drawback was that the key identifier in CENSUS is slightly different in format. It is a minimum 5 digit number, which is a
combination of the numerical state code and numerical county/place code. However, when the state and county codes in LEMAS is concatenated most numbers acquired are less than 5 digits. After the adjustment in the format the merging was completed. There still were some departments that did not have the FIPS place code, thus they were matched based on state, county, city and department names. The departments that could not be matched in any way were excluded from the data set.

One of the most time consuming and labor intensive merging processes was inclusion of cartographic boundary definitions to the other data sets. Unlike other merging processes, where a crosswalk data set that includes match variables was present, in this case all cases had to be matched on a case to case basis. Boundary variables are necessary geographic identifiers for determining the location of a place on a map. These variables made the spatial analysis possible. U.S. Census Bureau provides free access on its website to those boundary files in various formats for different divisions and subdivisions of each state. For each state, boundary files for counties and incorporated places (e.g. cities) were downloaded from the website. Those files were converted into SPSS statistical package format. Based on the state, county, and place name boundary files were matched for each case and added into the data set as boundary variables.

Also a map that incorporates all three levels of police jurisdictions was not available. In order to create such a map all three layers or maps were downloaded from the Census website. County layer map was available for the whole country including all states. The city and county sublevel layers were only available at state level. For that reason, first of all, city layer and county sublevel layer states were merged within the
layer using the merge function of the Arc View GIS software. After creating each layer for the whole U.S., all three layers were merged on top of each other. One important problem encountered by the researcher at the merging process was adding the police department level data into the maps’ database. When additional data is merged into a map and later that map is merged into another map, the Arc View Software, for some reason the researcher could not figure out, fills all missing data (cells shown with dots representative of missing information) with zeros. This serious problem, which creates problems especially for dichotomous variables, was solved by first merging the maps and adding the outside data in the merged map at the last step based on a unique identifier common to both the merged map and the additional data.

After the final map was created, department level data has been added into the map using Census provided Area Key as the unique identifier. Just as explained above, the same process of creating a unique identifier was used in order to compute the identifier in the final map’s database.