

EXAMINING THE RELATIONSHIP BETWEEN CRIME RATES AND CLEARANCE
RATES USING DUAL TRAJECTORY ANALYSIS

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DEDICATION

To Chris, for your unwavering support and encouragement, not only during this process but also throughout our entire relationship.

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LIST OF ABBREVIATIONS AND SYMBOLS

Akaike Information Criterion	AIC
Average posterior probability	APP
Autoregressive integrated moving average.....	ARIMA
Autoregressive moving average.....	ARMA
Bayesian Information Criterion	BIC
Bureau of Justice Statistics	BJS
Censored normal distribution model.....	CNORM
Confidence interval	C.I.
Estimated group probabilities	$\hat{\pi}$
Federal Bureau of Investigation.....	FBI
Inter-university Consortium for Political and Social Research	ICPSR
Law Enforcement Management and Administrative Statistics.....	LEMAS
National Crime Victimization Survey	NCVS
Odds of correct classification.....	OCC
Originating Agency Identifier.....	ORI
Proportion of sample assigned to group.....	P_j
Standard Metropolitan Statistical Area.....	SMSA
Uniform Crime Report.....	UCR
United States Department of Justice	U.S. DOJ

ABSTRACT

EXAMINING THE RELATIONSHIP BETWEEN CRIME RATES AND CLEARANCE RATES USING DUAL TRAJECTORY ANALYSIS

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Police agencies dedicate large amounts of resources, and place a great deal of importance, on criminal investigations and solving crimes. However, very stable clearance rates over time in the U.S., coupled with highly fluctuating crime rates begs the question of whether there is actually a relationship between these efforts and crime rates. Specifically, if police improve their ability to solve crimes, does this have any effect on crime rates over time? A deterrence relationship might indicate that an increase in clearance rates leads to a decrease in crime rates. However, while some prior research indicates evidence of a deterrent effect when examining the relationship between crime rates and clearance rates, other research using various methods has found that crime and clearance rates move in the same direction, or have found no clear relationship between crime and clearance rates.

This dissertation further explores the longitudinal relationship between crime clearance and crime rates using an innovative method known as dual trajectory analysis. Examining all police agencies with 100 or more sworn officers in the United States, dual trajectory modeling is carried out on clearance rates and crime rates for the offenses of homicide, robbery, aggravated assault, and burglary from 1981 – 2013. Findings show that while there are discernible longitudinal patterns of both clearance and crime rates, no clear relationship between crime rates and clearance rates emerges from the dual trajectory analysis for this sample (although some interesting findings are noted). Implications for understanding the relationship between crime and clearance rates are discussed, as well as ideas for future research.

CHAPTER ONE: INTRODUCTION

If police improve their ability to clear crimes through arrest and exceptional means,¹ does this have any effect on crime rates over time? The police as well as the public have long used arrest as a measure of performance. In particular, the clearance of homicide investigations has been one very public measure of police effectiveness, as the public may view homicide clearance as an indicator of the ability of police to detect and deter crime and catch perpetrators (Wellford, Cronin, Brandl, Bynum, Eversen, & Galeria, 1999). In police “Compstat” or other managerial meetings, both crime occurrences and the solving of crimes are regularly discussed (Weisburd, Mastrofski, McNally, Greenspan, & Willis, 2003). Moreover, within police organizational culture and practices, finding and arresting suspected offenders is viewed as effective and good policing, and are often used to measure the performance of officers (Lum and Nagin, forthcoming; Nagin, Solow, & Lum, 2015).

Police emphasis on arrest and the resolution (or clearance) of crime rests in a belief that arrest can deter and control crime. This belief has its roots in thinking by the philosopher Beccaria (1764), who hypothesized that deterrence involves three components - certainty, severity, and celerity of punishment. However, Beccaria and later

¹ Exceptional means as defined by the Federal Bureau of Investigation’s (FBI) Uniform Crime Reports (UCR) indicate crimes in which police know the offender, but no arrest is made due to offender death, refusal of cooperation of a witness or victim, or denial of extradition. The data I use in this study is from the UCR, which includes both arrests and exceptional means in its calculation of clearances. However, the UCR does not distinguish between arrests and exceptional means in their data.

scholars have found the most empirical support for certainty, rather than the severity of punishment. More specifically, Nagin (2013) argues for a refinement of this certainty principle—that certainty of punishment relies on the probability of a number of events occurring, most importantly, the certainty of apprehension. Indeed, research examining the deterrent effect of the certainty or severity of incapacitation find little evidence that incapacitation deters (Durlauf & Nagin, 2011; Nagin, 2013). Rather, the effect of certainty of apprehension is much more promising in crime reduction and control (Nagin, 1998; 2013). This revised certainty principle places the police at center stage in the deterrence equation. Thus, it is not far-fetched that police or the public believe that when the police can increase the certainty of apprehension by solving more crimes, then perhaps this might create a deterrence effect.

There is one more caveat to the certainty principle discussed by Nagin (2013). Deterrence is not merely caused by the certainty of apprehension but a would-be offender's perception of the possibility of apprehension. This is an important distinction, as research has questioned whether police can reduce and control crime by clearing cases and making arrests. Despite great fluctuations in crime rates since the 1970s, there has been incredible stability in the proportion of crime that is cleared. Some studies that have examined the relationship between aggregate arrest rates² and crime rates have not found evidence of a deterrent effect (Decker & Kohfeld, 1985; Jacob & Rich, 1980; McCrary, 2002), and studies that have looked at this relationship over time have methodological

² Some studies in the literature use arrest rates, whereas others use clearance rates. Arrest rates refer to the number of arrests per 100,000 population. The clearance rate includes the number of arrests, as well as crimes cleared by exceptional means. This calculation is the number of clearances divided by the number of crimes. The present study uses clearance rates. When I discuss the literature, I refer to the terminology and methods used in that study.

limitations (Blumstein et al., 1978; Durlauf and Nagin, 2011; Nagin, 1998; 2013).

Instead, research suggests that police fare better by preventing crime in the first place, or by affecting the perceptions of potential offenders with regard to the probability of their apprehension (Durlauf & Nagin, 2011; Lum & Nagin, forthcoming; Nagin, 2013; Nagin et al., 2015; see also reviews of police research by Lum, Koper, & Telep, 2011; Sherman & Eck, 2002; Weisburd & Eck, 2004).

Despite this, there continues to be a great deal of importance placed on, and resources dedicated to, investigations and solving crimes in policing, suggesting a relationship between clearing crime and levels of crime. Yet, over the past 35 years, yearly clearance rates (crimes cleared by arrest or exceptional means divided by the number of crime for any given year) in the United States for many serious property and violent crimes have remained relatively stable, at about 46 percent clearances for violent crimes and 17 percent clearances for property crimes (Braga, Flynn, Kelling, & Cole, 2011). Despite the stability of clearance rates, crime rates (defined as the number of crimes per 100,000 population) have fluctuated. For example, according to the FBI Uniform Crime Reports, the rate of robbery in 1960 was 60.1 robberies per 100,000 population. Robberies jumped to 172.1 in 1970, 251.1 in 1980, 256.3 in 1990 and dropped to 145 robberies in 2000 and further dropped to 112.9 in 2012 (U.S. DOJ, FBI, 2015). Similar fluctuations occurred for other types of crime. There was a rise in crime rates until about the 1990s, which then decreased over the past 20 years. A cursory examination of crime clearances and crime rates questions whether there is, in fact, a relationship between the two.

Research examining the relationship between crime rates and clearance rates has been fraught with methodological limitations. Researchers have attempted to examine this relationship using methods such as cross-sectional studies, and a variety of regressions for longitudinal analysis of panel data. However, cross-sectional studies are not useful to examine how this relationship unfolds over time, as these studies are unable to distinguish a causal relationship between crime rates and clearance rates. Crime rates and clearance rates may mutually affect one another as further discussed below.

Association of crime rates and clearance rates at any given time may reflect both forces, which is often referred to as the simultaneity issue (Nagin, 1978). Attempts to sort out this relationship require complex methods. Often, it is assumed that a deterrent relationship exists between crime rates and clearance rates, with crime rates decreasing when clearance rates increase. Regression analysis of longitudinal data is a widely accepted method of study of this relationship, with lagged relationships attempting to isolate one variable's effect on another. Nagin (1998; 2013) reviews this research and concludes that there is some support for a deterrent effect in the study of arrests and crime, although earlier studies failed to account for the simultaneity problem.

However, one approach that has yet to be used to examine the relationship between crime rates and crime clearances is the use of group-based trajectory modeling, which may shed more light on this discussion and is the focus of this dissertation. Criminologists often use trajectory and dual trajectory analysis to categorize developmental patterns of a large group of individual offenders to see more specific trends that may be masked by a general trend. Trajectory analysis is an innovative

method for all sorts of longitudinal data (see Jones & Nagin, 2007; Jones, Nagin, & Roeder, 2001; Nagin, 2005; Nagin & Land, 1993; Nagin & Tremblay, 2001; Nagin & Tremblay, 2005). In this study, trajectory analysis allows a large population--all police agencies with over 100 officers in the U.S.--to be categorized according to their specific crime and clearance rate trends, and then to determine whether those trends are related (which involves a method known as dual trajectory analysis). Nationwide total, or aggregated, crime and clearance rate counts may hide variations in trends of clearance and crime among individual police agencies that might give us further understanding of the relationship between crime and clearance rates. For example, while these national aggregated clearance rates have remained stable, particular agencies might show increases in clearance rates over time matched with decreases in crime rates. This might indicate a deterrent effect of an increasing trend of crime clearance. Examining these trends at the agency level may uncover more information about the relationship between crime rates and clearance rates and further, more understanding at the agency level about the relationship between investigative efficiency and crime.

Wellford has used single trajectory analysis for homicide clearances in an unpublished analysis.³ However, no study has ever used dual trajectory analysis to examine the longitudinal relationship between crime rates and clearance rates. While trajectory approaches do not resolve the simultaneity problem discussed above, it does provide a different perspective on this longstanding question.

³ Personal correspondence between Charles Wellford and Cynthia Lum.

Given what we know about deterrence, some possible relationships might emerge using trajectory and dual trajectory analysis. The first follows from the deterrence hypothesis directly: if a police agency clears more crimes, this may raise the perceived certainty of apprehension in that jurisdiction, causing crime rates to decrease over time. Police investigative activities or tactics may influence crime levels as well as the number of arrests. Possibly, a negative inverse relationship may occur – as crime rates increase, clearance rates decrease because high crime overloads police workloads. A second possibility is that crime rate and clearance rate trends look similar - when crime rates go up, so too do clearance rates. Here, police may be responding to an increase in the crime rate by increasing arrests and clearances. Conversely, when crime rates decline, so too do clearance rates decrease. Perhaps the police are clearing less crime, because when less crime occurs, the harder crimes are left to solve. A third possible relationship is that there is no clear relationship between crime rates and clearance rates over time within U.S. police agencies. Clearance rates may reflect some aspect of police organizations themselves, such as agency size, location, city versus rural, or population served. Thus, the relationship between crime rate trends and clearance rate trends continues to remain unclear, particularly at the jurisdiction level.

In this study, I use trajectory and dual trajectory analysis to explore the possibility of these relationships. This dissertation is part of a larger project, funded by the Laura and John Arnold Foundation,⁴ examining effective investigative practices using multiple methods, including trajectory analysis (see Lum et al., 2016). Rather than only examining

⁴ Cynthia Lum and Charles Wellford. Identifying Effective Investigative Practices: A National Study Using Trajectory Analysis. Laura and John Arnold Foundation (\$579,207).

homicide as others have done (Wellford et al., 1999; Borg & Parker, 2001; Cronin et al., 2007; Davies, 2007; Keel, Jarvis, & Muirhead, 2009; Regoeczi, Jarvis, & Riedel, 2008) or aggregate crime and clearance rates, the overall project examines clearance rate trends for the crimes of homicide, robbery, aggravated assault, burglary, larceny, and auto theft to identify agencies who may be using effective investigative practices. For this dissertation, I build on that analysis, focusing specifically on using dual trajectory modeling to examine the longitudinal relationship between four serious crime types (homicide, robbery, aggravated assault, and burglary) and their crime and clearance rates across agencies with 100 or more officers. Studying the relationship between other types of crime and their clearance rates over time may yield more understanding about the relationship between crime and clearance rates more generally. According to the 2014 UCR “Crime in the United States” report, of the 1,165,383 violent crimes that occurred in 2014, 1.2% were homicides, while 28% were robberies, and 63.6% were aggravated assaults. There were over 8 million property crimes in 2014, with burglaries accounting for 20.9%. Clearance rates are also much higher for homicide (64.5%) compared to robbery (29.6%), aggravated assault (56.3%), and burglary (13.6%) (U.S. DOJ, FBI, 2015), indicating potential differences in investigative practices by crime type. For example, a deterrent relationship may occur for robbery, in which clearance rates increase while the crime rate decreases. However, an increase in the clearance rate may not result in a reduction in the crime rate for burglary. Therefore, examining specific crimes rather than crime types totaled together as violent crime or property crime aggregates may allow more subtle nuances to emerge.

Overall, using dual trajectory methods may reveal important and missed nuances in the relationship between crime rates and clearance rates for individual police agencies that might be masked when examining national trends. Understanding whether there are variations in clearance rates for specific crimes across agencies with varying crime rates may be an important first step in then understanding investigative differences between agencies that have certain crime and clearance rate trends.

CHAPTER TWO: LITERATURE ANALYSIS

What is the relationship between clearance rates and crime rates? As discussed in Chapter 1, there could be an inverse relationship between crime rates and clearance rates, possibly indicating a deterrent effect if clearance rates impact crime. However, crime rates could also increase when clearance rates increase, perhaps suggesting that more crime may generate more crime solutions. The inverse may also be true, in which crime rates and clearance rates may decrease together. Alternatively, there may be little relationship between levels of crime and clearances of crime over time. In this chapter, I explore the research on the relationship between crime rates and clearance rates over time.

Increased Crime Clearances and Decreases in Crime: A Deterrence Relationship?

According to deterrence theory, we might expect that when police solve more crimes and arrest more perpetrators, both arrested offenders and other potential offenders might be deterred. Deterrence stems from the work of Beccaria (1764) and Bentham (1879). According to Beccaria and Bentham, deterrence consists of certainty, severity, and celerity of punishment. The certainty of punishment indicates that punishment will be imposed, severity is the harshness or length of the punishment, and celerity is the speed with which punishment is enacted. Much of the deterrence research today focuses on whether the certainty or severity of punishment acts as a general or specific deterrent to

prevent crime from occurring. General deterrence refers to the prevention of crime among the general population, whereas specific deterrence is focused on the actions of individuals. Thus, punishment exists to warn the general public from committing crime, but punishment is also specific to an individual who has committed a crime to prevent that individual from committing further crime.

In deterrence literature, a body of research focuses on the severity of punishment, such as the length of incarceration and severity-enhancing measures that include harsher sentencing penalties. These types of studies examine whether the threat of incarceration or the length or severity of sentencing reduces crime. However, the research suggests that the certainty of punishment is more important as a deterrent to crime than the severity of punishment. One reason, as Nagin (2013) argues, that punishment severity or certainty does not seem tied to crime rates is because the certainty of punishment relies on some conditional probabilities - the probability that an offender will be caught, tried, and incarcerated. Thus, the certainty of punishment begins with the certainty of apprehension, which is measured by law enforcement's ability to arrest offenders, thus "clearing" a crime.

Nagin's review (2013) concludes that there is more evidence of a deterrent effect of arrests on crime as compared to incarceration on crime and that crime prevention could be more cost effective by shifting current resources from incarceration to policing. This relies on a major assumption – that we can decrease both incarceration AND arrest. To achieve such a deterrent effect, Nagin argues that the emphasis should be on generating a perceived risk of apprehension, not increasing the severity of sanctions. One way to

achieve this is changing the number of police or the type of police activity. Studies examining the effect of police numbers on the crime rate has shown some evidence of a deterrent effect in both the increase in the number of police (see Di Tella & Schargrodsky, 2004; Evans & Owens, 2007; Klick & Tabarrok, 2005; Levitt, 1997; Marvell & Moody, 1996) and changes in police activity (see Kubrin, Messner, Deane, McGeever, & Stucky, 2010; Rosenfeld, Fornango, & Rengifo, 2007; Sampson & Cohen, 1988; Wilson & Boland, 1978 for studies on broken windows policing, also see Braga, Papachristos, & Hureau, 2012; Sherman & Weisburd, 1995 for hot spots policing studies). However, police activities and numbers may affect crime independently from the clearance rate. The majority of crimes do not result in an arrest; so perhaps crime clearance is not related to crime rates as much as is believed.

Before continuing, an important distinction needs to be made between arrest rates and clearance rates. The use of arrest rates are frequent in deterrence literature; however, this study uses clearance rates.⁵ The term “arrests” simply refer to the number of arrests made. The arrest rate is the number of arrests made by the police at any given time, divided by the population (and sometimes standardized to 100,000 persons). The clearance rate, however, is the number of crimes cleared by arrest or exceptional means⁶ divided by the number of crimes in any given period. The relationship between the two is not entirely clear because the clearance rate, unlike the arrest rate includes the number of

⁵ The terminology I use when reviewing the literature is what the researchers utilized in that study.

⁶ The proportion of arrests cleared by exceptional means is unknown in the UCR data, as the FBI does not distinguish between crimes cleared by arrest from those cleared by exceptional means in the data used in this study. Jarvis & Regoeczi (2009) analyze over 3,000 homicides obtained from the National Incident-Based Reporting System from 1996-2002 and find that nearly 11% of the homicides were cleared by exceptional means.

crimes in its calculation. For example, it is possible for the arrest rate to decrease, while the clearance rate remains stable as long as the proportion of arrests and crime remain the same. The reverse may happen as well – the arrest rate may increase, but the clearance rate will continue to be stable if the number of crimes also increases.

Thus, if arrest deters crime, then we might expect that as clearance rates increase (the proportion of crimes cleared by arrest or exceptional means) the crime rate will decline. Perhaps an increase in an agency's ability to solve crimes may prompt offenders to believe their risk of apprehension is higher, thus deterring them. Alternatively, perhaps more offenders are incapacitated, which may drive down crime rates since would-be offenders and recidivists are unable to commit crimes. Deterrence literature often finds a general deterrent relationship between arrests and crime rates (Nagin, 1998; Durlauf & Nagin, 2011; Nagin, 2013), although studies also show that jurisdictions might need to have a certain level of arrests and crime clearances before the perception of the risk of apprehension is felt by would-be offenders. Tittle and Rowe (1974), for example, examine the relationship between crime rates and arrest clearance rates (crimes cleared by arrest divided by crimes reported) using one year of data (1971) from Florida, consisting of both cities with populations over 2,500, and county data. They find that there is a deterrent relationship between arrest clearance rates and crime rates, but the clearance rate had to reach a certain percentage for the deterrent effect on crime to occur. Tittle and Rowe call this the tipping effect, which is "the ability of the police to clear a sufficient proportion of crimes through arrests to enable marginal increases in the quantity of arrests to deter potential offenders" (Chamlin, 1991, p. 187). In other words,

the clearance rate must hit a certain percentage for a deterrent effect to occur, in which the crime rate decreases. In this study, the arrest clearance rate had to be above 30 percent for a noticeable change in crime to occur. Therefore, a deterrent effect exists between arrest clearance rates and crime rates, but only once the clearance rate reaches 30 percent or higher.

Another cross-sectional study that focuses on finding the tipping effect of clearance at which a deterrent effect occurs was conducted by Brown (1978), who uses 4 data sets of crime and arrest data: California cities with over 25,000 population in 1971, California county data in 1973, as well as city and county data from Florida used by Tittle and Rowe (1974). Brown uses the same arrest clearance calculation used in Tittle and Rowe (1974) for the Florida data and California counties, but he uses two different measures for the California city data: the ratio of index arrests to reported crime (arrests divided by crime) and the ratio of persons charged with crimes to reported crime (charged divided by crime). He performs correlations on the data. The California data demonstrates a deterrent correlation between crime and clearance rates, but no tipping effect. However, there is evidence of a tipping effect in the Florida data, with the tipping effect occurring when the arrest clearance rate is at 30 percent or higher. Brown finds that the tipping effect is stronger in smaller cities and counties. The reason for this finding is unclear, but Brown offers three hypotheses: it may be a spurious effect, larger cities did not meet the tipping effect, and citizens in smaller cities may be more aware of the sanction threats. Based on Tittle and Rowe (1974) and Brown's (1978) findings, the tipping effect appears once the arrest clearance rate reaches 30 percent.

Additional cross-sectional studies look at the crime rate/clearance rate relationship among different crime types. Wellford (1974) examines the crime rate and clearance rate relationship with multiple correlation and regression models, using the 21 largest cities in the U.S. The data is from each of the UCR index crimes for the totals of property crime, violent crime, and total crime from 1960, 1970, and 1971. Wellford finds a moderate deterrent effect on the relationship between certainty of apprehension as measured by the clearance rate and crime rate for violent crime, property crime, and total crime.

Looking at several crime types, Geerken and Gove (1977) hypothesize that the deterrent effect should be strongest for property crimes, such as robbery, burglary, auto theft, and larceny because these are all highly rational crimes. The deterrent effect would be only moderate for rape, and low for homicide and assault because those are crimes that involve low rational thinking and are sometimes considered “crimes of passion.” The authors also examine the system overload hypothesis in which a negative relationship occurs because crime rates increase while clearance rates decrease, although they argue that this is most likely to occur after arrest and in the judicial processing stage. They believe that low volume crimes that are easily solved, such as homicide and assault, are unlikely to be affected by system overload. They use FBI data from 1970, 1971, and 1973 from SMSAs (Standard Metropolitan Statistical Areas) over 500,000. Their analysis includes the crimes of homicide and non-negligent manslaughter, aggravated assault, forcible rape, robbery, burglary, larceny, and auto theft. Again, they examine the correlation between crime rates and clearance rates (cleared by arrest) for these cities.

The findings are consistent with deterrence theory, not the system overload hypothesis. A deterrent relationship occurs for the property crimes, but assault and homicide clearances and crime move in the same direction. These results indicate that punishment may act as a deterrent, especially for rational crimes. However, the threat of punishment may not be a deterrent for crimes of passion. Again, it is important to keep in mind that these studies are a cross-sectional study design, which looks at one year (or three non-consecutive years) of data in multiple locations. A critique of using cross-sectional data is that such analyses do not demonstrate a temporal or even causal relationship between arrest/clearance rates and crime rates, only a correlational association.

One significant advance in the study of the deterrence relationship between arrest/clearance rates and crime has focused on improving the methods by which this relationship is examined and also examining the relationship over time. Chamlin (1991) further examines the tipping effect of arrest clearance rates on crime rates using longitudinal data from seven cities in Pennsylvania. He examines monthly counts of crime rates and arrest clearance rates for the offenses of robbery, burglary, grand larceny, and auto theft, with data from 1967 through 1980 using autoregressive integrated movement average (ARIMA) modeling. Only one small city in the analysis indicated a tipping effect occurred when arrest clearance rates reached 40 percent for robbery and auto theft, resulting in a decrease in crime rates. However, many cities did not have an arrest clearance rate over 40 percent for any offense. Chamlin's findings are in contrast to the two prior studies on the tipping effect, which indicated a tipping effect at 30 percent.

A study by D'Alessio & Stolzenberg (1998) examines the frequency of arrests as a measure of certainty of apprehension and the relationship with crime rates. They use data from Orange County, Florida using seven index crimes (homicide, forcible rape, robbery, aggravated assault, burglary, larceny-theft, and auto theft) as the measure of crime rate, and the frequency of arrests made by police as the arrest certainty measure. They measured crimes and arrests as aggregate counts of all offenses included in the study. The period examined for the data is a 184-day period in 1991. Analysis was conducted using vector autoregressive moving-average (ARMA) models, which allows for testing both contemporaneous and lagged relationships between variables. They find a deterrent relationship in which as the number of arrests made increase, the amount of criminal activity decreases significantly the following day. The contemporaneous findings indicate that crime is affecting arrests. Although it is not clear why there is a one-day lag in the deterrent effect, the authors suggest that news and media dissemination, as well as person-to-person dissemination, may play a role.

Despite evidence of deterrent effects in these studies, some questions remain unanswered. There is still not enough evidence to indicate at which point a tipping effect occurs. Some studies suggest that smaller cities are better able to clear crimes (Cordner, 1989; Paré, Felson, & Ouimet, 2007). The simultaneous nature of the relationship between crime rates and clearance rates is unresolved. The simultaneity issue assumes that crime rates and clearance rates mutually affect one another, but it is difficult to establish causality in the relationship. Several studies use cross-sectional analysis, which does not allow trends to emerge in crime rates and clearance rates over time.

Crime Rates Increase (or Decrease) with Increases (or Decreases) in Clearance Rates

This relationship indicates that crime rates and clearance rates are moving in the same direction. For example, as crime rates increase, so do clearance rates. This relationship may occur because as crime increases, more police may be hired to deal with the rising crime rates, which may lead to increases in case clearances (Levitt, 1996). This relationship might also reveal something about the nature of crime itself; the increases in crime may mean that there is more crime that is easier to solve (Tilley, Robinson, & Burrows, 2007) as would-be offenders take advantage of easy opportunities for crime (Nagin et al., 2015). Alternatively, if both arrests and crime increase, but if the rate of arrests increases more sharply, this will also increase the clearance rate. Here, police activity may be contributing to this phenomenon, as the police may be responding to an increase in crime (Decker & Kohfeld, 1985). Alternatively, the reason for an increase in crime and clearances may not be due to more crime occurring, but police are recording more or new categories of crime as they are cleared (Jacob & Rich, 1980). This could happen, for example, in the case of mandatory arrests for domestic violence. Another possible explanation for increased clearance rates coupled with increased crime rates is that as crime rates increase, there may be pressure to hire more police to do something about crime. This increase in police officers may increase the clearance rates as more police can make more arrests.

Decker and Kohfeld (1985) use homicide, robbery, and burglary data from the St. Louis police department from 1948-1978 to examine the relationship between crime rates and arrest rates (calculated per 100,000 citizens) specific to each offense, as well as raw

counts of crime and arrests also specific to each offense. They first review the relationship using the arrest rates and find no significant results between the relationship of arrests rates and crime rates. However, when they examine the relationship between raw arrest counts and crime rates, these findings indicate an increasing number of arrests in response to increasing crime. As crime rises, so does the number of arrests. They argue that arrests indicate how well police respond to an increase in crime.

Similarly, crime rates and clearance rates might also decline together. Some studies have found that when the crime rate decreases, so does the number of police (Tittle & Rowe, 1974). A reduction of police results in fewer officers to make arrests and clear cases. Cook (1979) suggests that when the crime rate decreases, so do cases that are more easily solved, which could also decrease the clearance rate.

Much of the research in this area is theoretical, without empirical studies to verify these hypotheses. Although Decker & Kohfeld (1985) find that increasing crime leads to increasing arrests, their finding applies only to the raw number of arrests and crime rates. However, an increase in arrests does not necessarily result in an increase in the clearance rate. The clearance rate may decline if the proportion of crime rises faster than arrests. Some research suggests that higher crime may lead to a higher amount of police (Levitt, 1996), but police activity may also play a role in increasing crime rates. The reverse in this directional relationship has also been found (see Tittle and Rowe, 1974). However, the actual reason for these findings is still unclear, as is the effect on the clearance rate.

Crime Rates and Clearance Rates are not Related

National clearances have remained remarkably stable over time, despite significant fluctuations in crime rates. Thus, the proportion of crimes cleared by arrest or exceptional means seems to remain the same, whether we are in a period of very high crime or lower levels of crime. This may suggest a third relationship between clearance rates and crime rates – perhaps the ability of agencies to clear crimes as measured by the clearance rate, does not impact crime rates at all. Similarly, this empirical finding may also indicate that no matter the level of crime, police agencies seem to continue to resolve approximately the same proportion of those crimes (except homicide, which has seen significant declines in its clearance rate over time). Perhaps for various crime types, there is simply a “natural” rate of clearance—a set proportion of crimes that are amenable to being resolved. Some studies have found no relationship between crime rates and clearance rates, or mixed findings with some crime showing a relationship one way, and other crimes moving in the opposite direction. In these studies, it is often not possible to draw any conclusion about the relationship.

For example, Greenberg and Kessler (1982) examine seven index crimes and their clearances in 98 cities with over 25,000 population from 1964-1970. They used estimation models that examined both instantaneous and lagged effects. There is no consistent relationship found between crimes and clearances among the offenses. For the effect of crime on clearance rates, only homicide demonstrated a negative relationship, while the remainder of crimes had no relationship. The effect of clearances on crime indicated a negative relationship for burglary and aggravated assault and no effect for homicide. Additionally, Greenberg, Kessler, and Loftin (1983) extend the analysis to

examine whether increases in police employment reduces violent or property crime. No relationship was found between the two variables. They argue that small changes in police numbers are unlikely to be observed by potential offenders, which will not act as a deterrent to lead to crime reductions.

Chamlin (1988) examines data from Oklahoma City and Tulsa, Oklahoma. UCR data is used for the number of crimes and arrests per month of robbery, burglary, grand larceny, and auto theft from 1967-1980. He uses an autoregressive integrated moving average (ARIMA) time series because this model can identify lag structures, accounts for seasonal variation, and have increases in reliability in model parameter estimation. Only robbery arrests had a deterrent relationship on the robbery crime rates. There was no relationship found for the other three crimes examined.

Using the Cincinnati race riots to determine whether changes in the crime and arrest relationship occur, Chamlin and Myer (2009) examine the relationship between crime and arrests to examine further how contextual factors may influence this relationship. They used monthly police data from 1997-2005 in Cincinnati. The riots occurred in April 2001. Disaggregated numbers of crime and arrests for robbery, burglary, auto theft, and larceny are examined, using ARIMA techniques to complete the analysis. They find no relationship between crime and arrests, using the aggregate of their four crime measures. A deterrent effect was only found in the district in which the riots occurred once this variable was controlled for, and the authors suggest it is important to consider how certain social and contextual factors may influence the crime-arrest relationship.

The studies in this section are longitudinal and offer an improvement in methodology over other cross-sectional studies. Despite the improved methodology, these findings offer no conclusions on the relationship. This relationship may also be complex due to the type of offense. As others have demonstrated, more violent crimes with higher victim contact tend to have higher clearances, whereas low victim contact property crimes have low clearances (Geerken & Gove, 1977; Tilley et al., 2007). Therefore, variations due to the offenses themselves provide difficulties in disentangling the relationship between crime rates and clearance rates.

Continuing to Examine the Relationship between Crime Rates and Clearance Rates using Dual Trajectory Analysis

Deterrence literature has examined the relationship between crime and clearances, with an interest in whether police can have an effect on crime. Some of the research indicates that police can affect crime: the relationship between clearance and crime rates demonstrates a deterrent effect. Literature also shows instances in which crime and clearances move in the same direction, or simply no clear relationship between the two. The relationship between crime rates and clearance rates is not completely clear.

The variation of findings demonstrates the theoretical complexities of this relationship that have not yet been clearly sorted out. The deterrence hypothesis indicates that an increase in clearance results in a decrease in crime rates. However, the police may be overloaded by high crime, which results in a decrease in clearances. It is possible that an increase in clearances may increase crime as well, as police activities may record more crime (Jacobs & Rich, 1980). Conversely, rising crime may encourage police to contribute more resources to this problem, thereby increasing arrests (Decker & Kohfeld,

1985; D'Alessio & Stolzenberg, 1998). When crime falls, this may decrease the clearance rate as well, as only more challenging cases are left to clear (Cook, 1979). Or, police may simply contribute fewer resources to crime when the crime rate is low, resulting in a lower clearance rate. Crime rates and clearance rates may also not be related at all. There may be other factors that affect this relationship.

The studies described above use many different methodological approaches in examining the question. These include cross-sectional studies and panel studies with correlation analyses and a variety of regression analyses. Cross-sectional studies are not as useful because they cannot identify changes in the relationship over time. Instead, it is only one snapshot in time, which does not fully describe the relationship, providing only an average of the relationship without completely allowing trends to emerge. Fisher and Nagin (1978) conclude that a deterrent effect is very unlikely to be identified with the use of cross-sectional data. This is because cross-sectional studies cannot untangle the simultaneous relationship of crime rates and clearance rates. To separately examine the relationship that each variable has on the other, researchers must use methods such as two-stage least squares or simultaneous equation models that make assumptions called “identification restrictions” (Nagin, 1978). However, correctly identifying these assumptions can be challenging, and misidentifying the assumptions can lead to incorrect conclusions about deterrent effects (Nagin, 1978). These assumptions introduce variables commonly referred to as instrumental variables that affect the independent variable, but not the dependent variable; introducing this additional information into the analysis theoretically enables an analyst to statistically “identify” (i.e., distinguish) the effect of

the former on the latter. However, Nagin notes that. “The restrictions used to identify the crime-generating function are often implausible, consequently raising serious doubts as to the interpretability of the estimated parameters” (Nagin, 1978, p. 363). Nagin (1978) argues that studies must have a time-series component in the data to attempt to measure the deterrent effect of clearance rates on crime.

Longitudinal studies offer an improvement over cross-sectional research, but it is important to note critiques with these methods as well. Many of the prior longitudinal research only looks at one city or agency, or a small number of cities or police agencies. The findings from these studies may not generalize well to other areas. Additionally, the conflicting results of the studies may suggest that the relationship is affected by the context of the situation and the area under study. Many factors can influence how crime rates and clearance rates affect each other; therefore, the outcomes of the relationship may vary across contexts and places.

Additional critiques relate to the clearance rate itself. Despite its frequent use in research, there are debates about using the clearance rate as a measure of effectiveness for police or investigator performance. Cook (1979) argues that clearance rates are not an effective measure of criminal justice system effectiveness. A criticism of the UCR measurement is no distinction exists in the UCR between cases cleared by arrest or exceptional means, and cases cleared by exceptional means may inflate police agencies’ clearance numbers (Jarvis & Regoeczi, 2009). The UCR (U.S. DOJ FBI, 2015) defines an exceptional means clearance as one in which police identify the offender, but cannot make an arrest due to some factor outside the control of law enforcement. Another

problem with clearance rate data is that crimes that occurred in one year may be solved in another year, which may result in a clearance rate over 100%. Finally, the calculation of the clearance rate itself may suffer from measurement error. The denominator in the clearance rate calculation contains crime counts, and official crime counts such as the UCR may underreport, as the UCR only includes crimes reported to police. As Gibbs and Firebaugh (1990) discuss, this may produce a measurement error in which the relationship demonstrates a negative correlation because crime counts are understated, whereas the numerator of clearances is overstated. Despite these criticisms, UCR clearance rates are still used frequently in deterrence research, as it continues to be one of the few indicators available that measures investigative effectiveness (Cordner, 1989). The large number of agencies that report clearance rates to the UCR also provides researchers easy access to these data.

As an extension of prior research, the present study uses longitudinal data to examine the relationship between crime rates and clearance rates. Using over 30 years of data can provide a better picture than cross-sectional studies and shorter longitudinal studies in the relationship over time. This study also uses a method not used in previous research to explore the relationship between clearance rates and crime rates – group-based trajectory modeling. Trajectory modeling can categorize police agencies according to their crime rate and clearance rate trends. This can unmask variations in police agencies' crime and clearance trends that are not evident from the national average. Dual trajectory analysis may reveal whether there is a connection between the long-term crime rate trends of agencies and their long-term clearance rate trends. This method has never

been used to examine the crime rate/clearance rate relationship. Based on the conflicting theoretical findings above, dual trajectory analysis may be useful in demonstrating the variation of this relationship among different agencies, and possibly lead to the development of hypotheses about why the trend differs from place to place. While other studies tend to focus on homicide or all index crimes, this study will concentrate on three crimes that police most frequently encounter: robbery, aggravated assault, and burglary, as well as homicide, which is often a marker of police effectiveness.

CHAPTER THREE: RESEARCH DESIGN

This study uses trajectory analysis and dual trajectory analysis to examine further the relationship between crime rates and clearance rates of jurisdictions with law enforcement agencies with at least 100 sworn officers. First, trajectory analysis will be used to determine if individual law enforcement agencies mirror the national trend of stable clearance rates, or if they vary in their trends (and if those variations can be grouped). Again, the use of trajectory analysis to analyze case clearances is part of the broader funded project of which this dissertation is a part. Then, trajectory analysis will be used to determine if there are variations in crime rate trends at the agency level. Finally, dual trajectory analysis will be used to determine if an agency that has a certain clearance rate trend also has a similar crime rate trend. Dual trajectory analysis allows researchers to examine two temporal trends for many units of analysis, grouping those units (in this case, police agencies) into similar trends over time. Using trajectory analysis also provides a useful visual representation of various categories of clearance rate trends across hundreds of police agencies. Dual trajectory analysis allows us to see if a second trend (in this case, crime rates) for each agency is connected to clearance rate trends.

Data Source

Annual crime rates and annual clearance rates for all agencies with at least 100 officers are needed for an extended period to conduct this study. This data can only be

found, for all agencies, in the Uniform Crime Reports (UCR), collected each year by the Federal Bureau of Investigation (FBI) since 1930 and now housed in raw data form at the Inter-university Consortium for Political and Social Research (ICPSR) website.⁷ Specifically, the data used in this study derives from the “Offenses Known and Clearances by Arrest”⁸ summary data as reported to the UCR program by police agencies (U.S. DOJ, FBI, 2015). The “Offenses Known and Clearances by Arrest” is an annual collection of data from individual law enforcement agencies across the United States. The law enforcement agencies include city, county, state, federal, tribal, and college/university agencies. These agencies may report to a state reporting program, which in turn reports to the UCR program, or directly to the UCR program itself. Currently, 47 states use a state reporting program to report to the UCR (U.S. DOJ, FBI, 2015) and agencies in the remaining states report directly to the UCR program. Police agency participation in the UCR program is voluntary.

One criticism of the UCR involves whether it is a valid measure of crime in the United States. The National Crime Victimization Survey (NCVS) data sometimes differs from reported offenses in the UCR (Cork, Cohen, Rand, & Rennison, 2002). The NCVS is a survey administered to households in the United States each year to measure criminal victimization experienced by individuals, whether reported to the police or not (Truman & Langton, 2014). Despite these criticisms, Gove, Hughes, and Geerken (1985) find that both the police statistics and citizens are in agreement about how violent crime is defined,

⁷ <http://www.icpsr.umich.edu/icpsrweb/landing.jsp>

⁸ The title of the report is slightly misleading regarding the clearances by arrest. The FBI does not distinguish between clearances by arrests or exceptional means, although it does allow reporting of exceptional means as cleared.

with homicide, robbery, burglary and motor vehicle theft in substantial agreement. There is less agreement between citizens and police among the definition aggravated assault, rape, and larceny, but the authors interpret this as an underreporting of non-stranger contacts with assaults and rape. The authors conclude that the UCR is a valid measure of violent crime. Additionally, another issue is that the UCR only includes crimes reported to the police, which is an undercount of the actual crimes that occur.

Despite this criticism, the UCR is the only source of year-to-year numbers of crimes and clearances for almost all police agencies in the United States. According to the UCR website, there are currently over 18,000 agencies that report their crime numbers to the UCR (2015). Even with the problems of missing data discussed below, there are still a large number of agencies in which there exist many years of reported crime, allowing for longitudinal analysis. Second, the UCR data comes directly from police agencies themselves, which is important as this study focuses on the relationship between crime rates and clearance rates using police agencies as the unit of analysis, and may also provide clues on investigative efficiency.

The UCR data contain the month-to-month raw number of crime offenses for eight index crimes (murder and non-negligent manslaughter, forcible rape, robbery, aggravated assault, burglary, larceny-theft, motor vehicle theft, and arson), as well as the number of clearances for each index crime. The UCR defines clearances as cases closed by arrest or exceptional means (U.S. DOJ, FBI, 2015). A case is cleared by arrest when it meets these three criteria: at least one person has been arrested, charged with the offense, and turned over to the court for prosecution. A case is cleared by exceptional means if it

meets one of the following criteria: police identify the offender, police gather enough evidence to make an arrest and turn over to the prosecution, police identify the suspect's exact location to take the suspect into custody, or a circumstance outside of law enforcement control prevents an arrest from occurring. An outside circumstance indicates that police have identified the offender of the crime, but cannot make an arrest due to offender death, refused cooperation of a witness, or denial of extradition (U.S. DOJ, FBI, 2015). Because the FBI does not distinguish between a case cleared by arrest and one cleared by exceptional means, the proportion of cases cleared by exceptional means to total crimes cleared is unknown.

Selecting an appropriate period for this study was driven by the quality of the UCR data over time. Although the FBI has been collecting this data since 1930, the data was not available to the public until 1964. Further, not all data for each jurisdiction for each year has been collected consistently. Figure 1 shows the number of agencies in the UCR dataset over time. As the figure demonstrates, before 1980, many agencies were not reporting their crime and clearance statistics to the FBI. Because of these reporting issues and missing data problems before 1980, this study only includes UCR data from 1981-2013.⁹ This provides over 30 years of data, which is sufficient for analyzing longitudinal data.

⁹ At the time of this analysis, only data up to 2013 was fully available in the UCR.

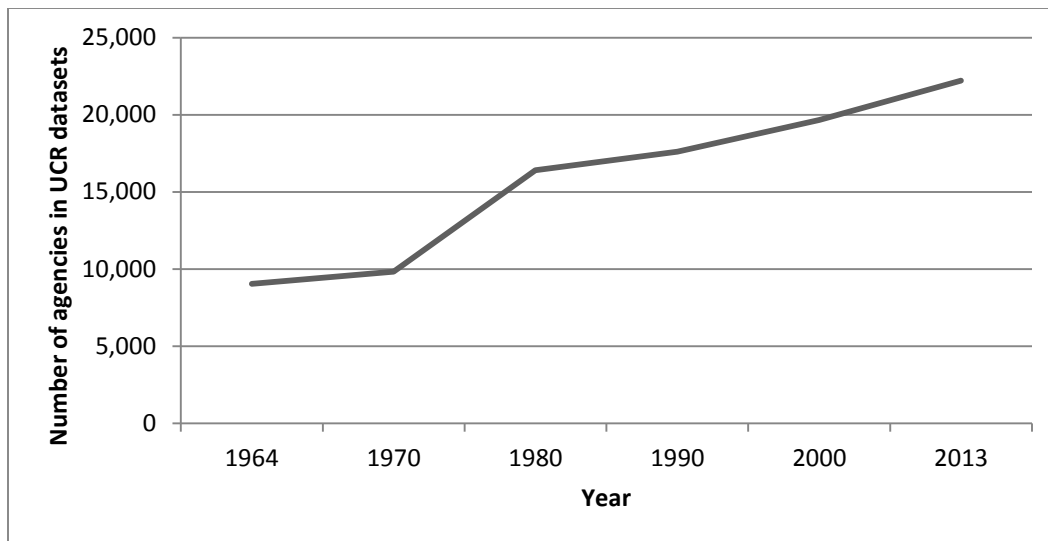


Figure 1. Number of Agencies in the UCR¹⁰

Even after 1980, many agencies do not report their offense and clearance statistics to the UCR. One major problem related to this is that the UCR does not distinguish between data that is missing and an actual count of “zero.” Thus, agencies in the UCR that indicate zero robberies in a particular year may have had zero robberies, or may not have reported their robbery statistics to the UCR. Because the UCR does not distinguish between these two options, the implications of missing data for research are serious and are discussed further below. Early on in this project, I decided only to include agencies with 100 or more authorized sworn officers to eliminate smaller agencies initially with many ambiguous zero values in the UCR. I identified these agencies by linking the Law Enforcement Management and Administrative Statistics (LEMAS) 2007 dataset (see U.S.

¹⁰ The number of agencies in the raw UCR “Offenses Known and Clearances by Arrest” data. Not all of these agencies reported to the UCR, as shown by the number of zeros throughout this data.

DOJ BJS, 2007) to the UCR data, which identifies the number of agencies with 100 or more authorized sworn officers.¹¹

Data Processing

The unit of analysis in this study is every law enforcement agency which reports to the UCR that has 100 or more authorized sworn officers. To carry out dual trajectory analysis of homicide, robbery, burglary and aggravated assault across agencies, the raw monthly UCR counts of crime for each offense type had to be converted to yearly counts of crime, then to crime rates (total yearly crimes divided by the population then multiplied by 100,000). Similarly, the monthly UCR counts of clearances had to be summed for each year and then converted to a “clearance rate” (the number of clearances for any particular year divided by the number of crimes for that year). UCR records this raw data by year, so this process was repeated for every year from 1981 to 2013.

The yearly UCR datasets contained the ORI number, demographic information for each agency listed (i.e., type of agency, location of the agency, jurisdiction population), and the monthly offense counts and clearance counts. The UCR specifies monthly crime and clearance counts by different subcategories. For example, within robbery counts, the UCR specifies “gun robbery,” “knife robbery,” “strong-arm robbery,” and “other weapons robbery” (and similarly with the clearance counts). Burglary categories included “forcible entry,” “unlawful entry where no force is used,” and “attempted forcible entry.” The data also provides for an “actual number of robbery total” and “total cleared robbery” (and similarly for burglary). For this study, the total crime

¹¹ At the time of this analysis, the 2007 LEMAS was the most recent year available.

count and cleared crime counts were used for robbery and burglary. Regarding assaults, this study examines index crimes only, which includes aggravated assaults. Because the total number of assault offenses and clearances included simple assaults, I removed the simple assault category. The remaining assault subcategories are considered aggravated assault. I added these assault subcategory variables together instead of using the “total” category. Assault offenses consisted of “actual number of gun assaults,” “actual number of knife assaults,” “actual number of other weapon assaults,” and “actual number of hand/feet assaults.” Assault clearance counts included “total cleared gun assault,” “total cleared knife assault,” “total cleared other weapon assault,” and “total cleared hand/feet assault.” Homicides are classified as “murder,” which includes murder and non-negligent manslaughter. I use this category to represent homicides. I then added these total monthly counts together to calculate the yearly total crime and clearances for offense type.

However, the variable of interest in this study is the clearance *rate*, not the clearance counts per year. I calculated the clearance rate for each crime type by dividing the total number of crimes cleared for a particular year by its corresponding total count for crime. This was done for each of the 33 yearly data sets and each crime type. Table 1 illustrates this three-step data process described above, which was conducted for each crime type of interest (homicide, robbery, burglary and aggravated assault).

Table 1. An Example of Steps Taken to Transform the Data, Using Burglary Data from Two Agencies

Step 1: Initial data broken down by month	ORI	Jan: Actual # of burglaries total	Jan: Cleared Total Burglary	Feb: Actual # of burglaries total	Feb: Cleared Total Burglary
	Agency X	74	19	74	26
	Agency Y	30	6	24	12
Step 2: Calculated number of crimes, clearances, and clearance rate	ORI	Burglary Offenses 1981	Burglary Cleared 1981	Burglary Clearance Rate 1981	
	Agency X	883	230	0.26	
	Agency Y	323	190	0.59	
Step 3: Merge yearly clearance rates into one dataset by crime (years 1981-2013)	ORI	Burglary Clearance Rate 1981	Burglary Clearance Rate 1982	Burglary Clearance Rate 1983	Burglary Clearance Rate 1984
	Agency X	0.26	0.26	0.28	0.17
	Agency Y	0.59	0.30	0.37	0.28

The other variable of interest is the crime rate. The crime rates for each crime type also needed to be calculated for purposes of the dual trajectory analysis. Crime rates are defined as the number of crimes per 100,000 inhabitants (U.S. DOJ, FBI, 2015) for each crime type for each year. I used the population variables reported in the yearly UCR data. There are three population fields reported in the UCR data (Population 1, Population 2, and Population 3). Three population fields exist because some cities overlap into multiple counties. Therefore, if a city is located in two different counties, then the first population variable refers to the largest segment of its jurisdiction, and the second and third population variables reference the other part of the jurisdiction. However, most agencies have their entire population within the first population field, not the second and third fields. The other two fields are “0” if the agency does not overlap into other jurisdictions.

The total agency population is the sum of the three population variables, which I used to calculate the crime rate. To obtain the crime rate, I followed similar steps as illustrated in Table 1 with the clearance rate. I summed the monthly crime counts into the number of offenses per year. I took that number, along with the population for that year and calculated the crime rate. The crime rate calculation is the number of offenses a year divided by the population of that year multiplied by 100,000. Finally, I created a crime rate dataset similar to the clearance rate set with the calculated crime rates from 1981-2013. At this point, I merged the clearance rate and crime rate data into one dataset per crime.

After completing this data processing, I conducted several steps to deal with the missing data. As mentioned above, the UCR contains many zeros that are ambiguous; some indicate a true zero number of crime or clearances, while for other agencies, a zero value was a missing value. This problem is compounded when summing across the data, as well as when calculating the clearance rate. Dividing clearances by zero would return an undefined value. Additionally, issues with some of the state reporting agencies result in some missing reports with many agencies within that state over an extended period. This is evident in jurisdictions with fewer officers, and also certain states, for example, Illinois.

To manage this issue, I first deleted all of the Illinois agencies, due to a large number of missing data from those agencies.¹² Missing data was also a problem with the

¹² Illinois agencies were missing between 17-33 years in the assault and burglary data, and 11-33 years in the homicide and robbery data. The Illinois agencies would have all been deleted based on the missing data rules I applied.

Florida agencies for aggravated assault data.¹³ I deleted all the Florida agencies in the aggravated assault data. Then, I examined each dataset and deleted other agencies that continued to have missing data across 10 or more years, as well as agencies with 7 or more consecutive years of missing data.¹⁴ For three agencies in the aggravated assault and one agency in the robbery data, I changed one entry in one year each to missing due to abnormally high clearance rates that appeared to be an error in the raw UCR data.¹⁵ Therefore, the entry for that year in that agency was simply missing and did not affect the overall missing data rule.

Since the crime rate data was already linked to the clearance rate data that took care of much of the missing data problems that may have existed in the crime rate data. However, instead of treating the zeros as missing, I left the zeros in for the crime rate data so just the missing designated data was eliminated for the crime rate datasets.¹⁶ I also checked the crime rate data using the 10 or more years of missing data rule, followed by the 7 or more consecutive years of missing data. This only resulted in a few deletions of agencies in robbery, assault, and burglary that were not deleted in the clearance rate data. I changed these few agencies to all system missing for the crime rate data. Next, I examined the crime rate data for outliers. I found 11 instances of outliers in the

¹³ All agencies in the Florida assault data were missing at least 20 years of data, and would have been deleted due to this missing data rules applied.

¹⁴ Some agencies did not report for the full year, according to the variable in the UCR that marked the number of months reported. This variable designation indicates the last month reported, so a “12” would indicate an agency reported in December. I did not adjust for those agencies that did not report all months. Using the burglary data, since that is the largest amount of data with 757 cases, an average of 3% of agencies did not report a full year (indicated by “12” in the UCR variable code).

¹⁵ These outliers were in the 1993 dataset, and one assault was in the 1988 data. These appear to be input errors in the raw UCR data, with the number of clearances or crimes entered as 999 or 9999. These numbers made the clearance rate over 1000%.

¹⁶ It seems possible that some of the smaller agencies may have had zero crimes occur that year, especially homicides.

aggravated assault data, and two each in burglary and robbery, and 1 in homicide.¹⁷ As before with the clearance data, that instance was simply changed to system missing for that agency for that year.

While trajectory analysis can accommodate some missing data (Nagin & Tremblay, 2001), there is no set guideline to determine the amount of missing data acceptable. The missing data processing I followed is intended to minimize the missing data as much as possible while retaining a large sample size. Table 2 displays the final sample size for the clearance rates and crime rates for each offense.

Table 2. Final Sample Size by Offense

	Clearance Rate	Crime Rate
Homicide	519	519
Robbery	729	728
Aggravated Assault	673	668
Burglary	757	755

Trajectory and Dual Trajectory Analysis

I used dual trajectory analysis to examine the relationship between clearance rates and crime rates. Trajectory analysis is a group-based modeling approached using time or age data that allows for longitudinal data with large numbers of units of analysis (in this case, police agencies) to be grouped by their similar longitudinal patterns (Nagin, 1999; Nagin, 2005). It is based on a semiparametric, group-based modeling strategy, and is similar to hierarchical modeling and latent growth curve modeling (Jones et al., 2001).

¹⁷ All instances of outliers were in the 1993 dataset and again appeared to be errors in the raw data with the number of crimes entered as 999 or 9999.

Often, trajectory analysis is used in developmental criminology to examine groupings of individuals according to their different offending patterns over their life course. Others, like Weisburd, Bushway, Lum, and Yang (2004) and Weisburd, Groff, and Yang (2012) employed trajectory analysis to examine crime rates at hot spots over time. Trajectory analysis is especially useful for exploratory analyses and developing hypotheses to explain differences across certain groups (Nagin, 2005). For example, in the case of Weisburd and colleagues (2004), some street segments showed sharp increases in crime over time, others stayed stable, and some showed decreases in crime over time. The benefit of trajectory analysis over other longitudinal statistical methods is that trajectory analysis places similar cases into trajectories that allows for comparisons between different trajectories (for example, trajectories with crime data can be classified as declining, rising, steady, etc.). It also provides a visual representation of the trajectories for further exploring the data. In this study, for example, one could see groupings of agencies that might follow the national trend, with stable burglary clearances over time. However, there may be other agencies that show, since 1981, a sharp decline in burglary clearances while others might show consistent improvement in clearance rates since the 1980s.

Trajectory analysis will display a visual representation of the trajectories, which may demonstrate a deviation from the average clearance rate or crime rate trend. The average clearance rate trends for the sample of the study for each offense remains relatively stable among all crimes, except homicide (see Figure 2). Homicide begins at over 80% clearance and falls slightly to under 80%. Aggravated assault remains

relatively stable around 60% clearances. Robbery fluctuates slightly, beginning just over 30% clearance and increasing to near 40%. Burglary remains stable at around 15-18% clearance. A trajectory analysis for each crime clearance rate may show how some agencies deviate from these averages. Agencies may improve or decline in clearances over time instead of following a stable trajectory.

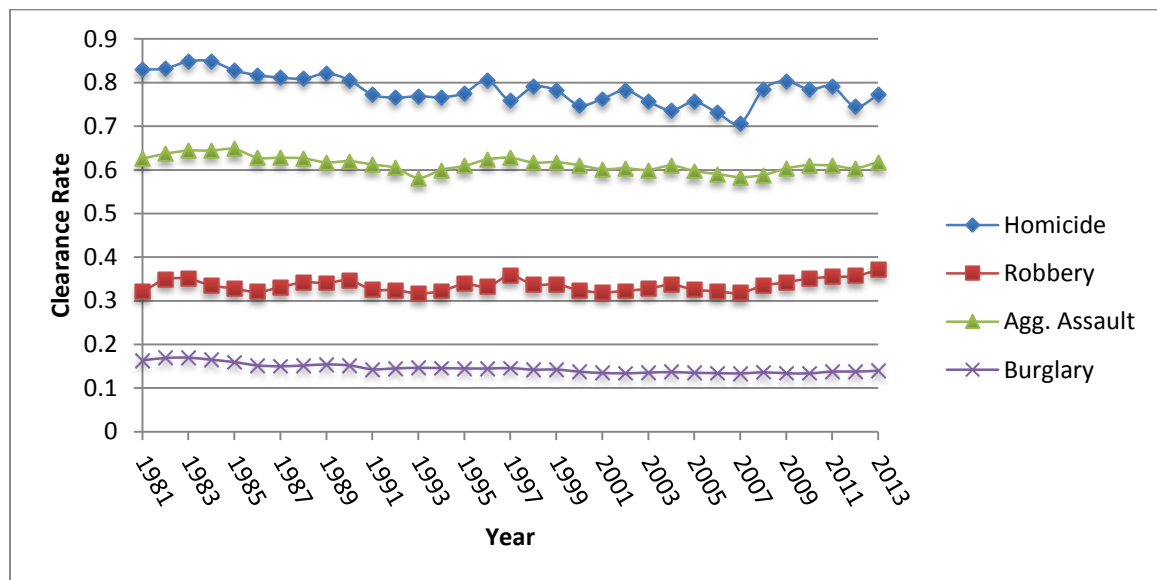


Figure 2. Average Crime Clearance Rates from 1981-2013 for Sample

The average crime rate trend shows more fluctuation than the clearance rate averages (see Figure 3). Burglary experiences a steep decline, beginning at 1,800 crimes per 100,000 population but drops to 700 crimes per 100,000. Aggravated assault has a slight bump – it starts at 300 assaults per 100,000, increases to over 400 assaults, then drops to just above 200 assaults per 100,000. Robbery experiences less fluctuation, commencing at 200 robberies per 100,000, increasing slightly over 200, and ends beneath

200 robberies per 100,000. Although homicide appears stable, the homicide crime rate is too low to be distinguishable on this graph. Figure 4 displays the homicide crime rate average, which shows much more fluctuation in the average than Figure 3. The homicide crime rate starts at 11 homicides per 100,000, experiences a decrease followed by an increase before dropping to around seven homicides per 100,000. Trajectory analysis of the crime rates may also demonstrate police agency differences in their crime rates. Some agencies may follow similar trends while other agencies may experience higher or lower crime rates. Obtaining clearance rate trajectories and crime rate trajectories allow for the dual trajectory analysis to occur.

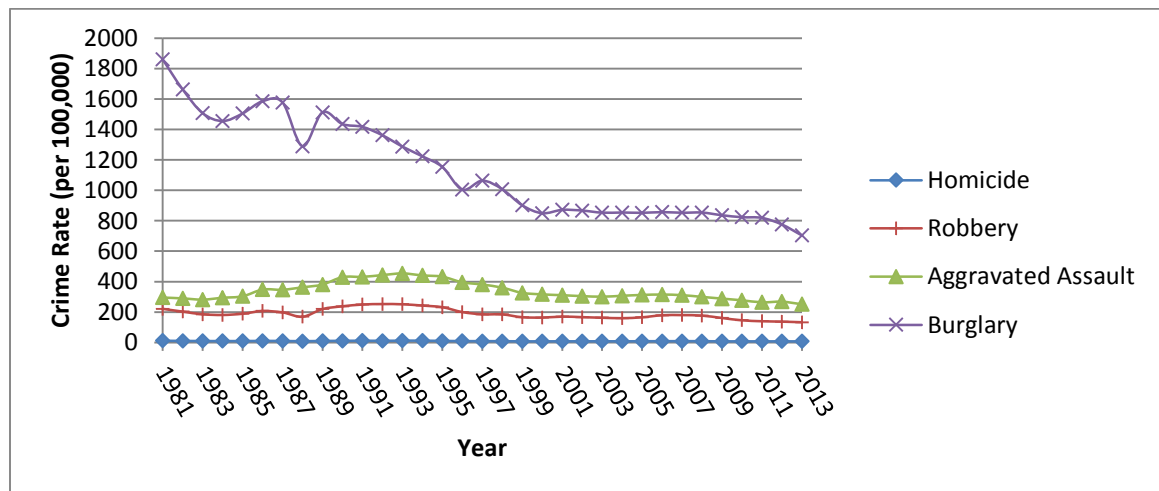


Figure 3. Average Crime Rates from 1981-2013 for Sample¹⁸

¹⁸ The crime rates and clearance rates used in this dissertation are not weighted averages. Therefore, the crime rate and clearance rate trends among my sample are slightly different from the national average.

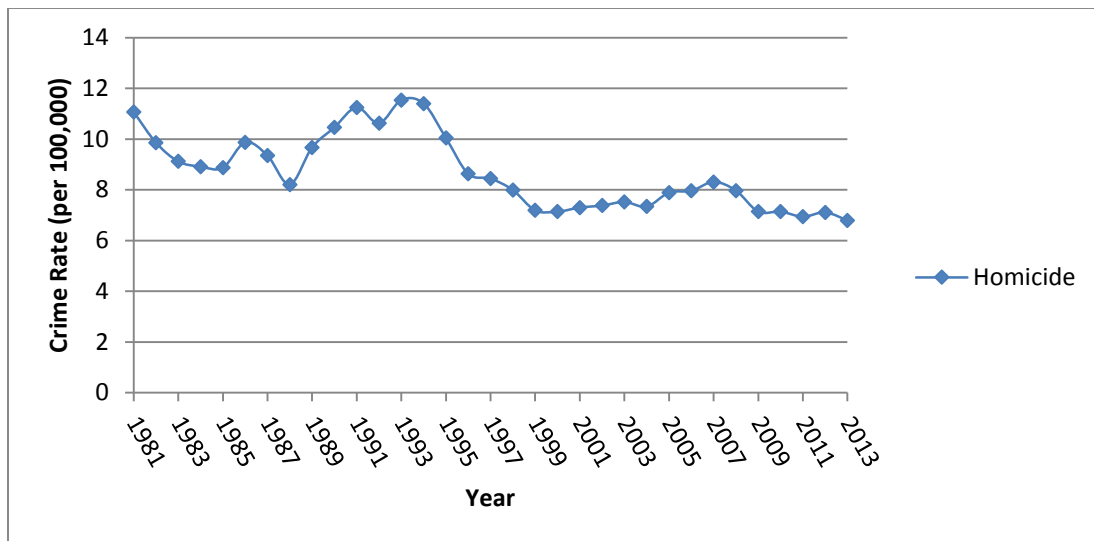


Figure 4. Average Homicide Crime Rate from 1981-2013 for Sample

Findings from the trajectory analysis of clearance rates are reported here, and in Lum, Wellford, Scott, and Vovak (2016). The contribution of this dissertation is the dual trajectory analysis of clearance rates against crime rates. Dual trajectory analysis is an extension of trajectory analysis. Dual trajectory is useful in demonstrating the relationship of two measures over time. This type of analysis is especially beneficial to examine “the connections between...trajectories of two outcomes that are evolving contemporaneously” (Nagin, 2005, p. 141). Dual trajectory “advances conventional approaches to measuring comorbidity or heterotypic continuity by providing the capability to examine the linkage between the dynamic unfolding of the two behaviors over the entire period of observation” (Nagin & Tremblay, 2001, p. 20). In other words, dual trajectory examines two trends over time and how these trends may link at given time points. Dual trajectory analysis is often used to examine offending patterns of individuals over the life course; however, Yang (2010) has used dual trajectory to

examine violent crime and disorder. According to Jones and Nagin (2007), dual trajectory analysis offers trajectories for both measurements (in the case of this study – crime rates and clearance rates), the probability of membership in each trajectory group, and the probability of linking memberships across behaviors or time. Dual trajectory analysis produces the probability of membership in a clearance trajectory given membership in a crime rate trajectory, the probability of membership in a crime rate trajectory given membership in a clearance rate trajectory, and the joint probability of belonging to a clearance rate and crime rate trajectory. Nagin (2005) argues that dual trajectory is superior to other longitudinal analyses because it provides overlap of variables, and using multiple probabilities, can indicate averages and deviations from the averages as well.

Proc Traj¹⁹ is an add-on to SAS statistical software and is used in this study to model trajectories. Both trajectory and dual trajectory analyses involve several steps before revealing the groupings of units of analysis or analysis of relationships. Nagin (2005) offers a detailed discussion of this process. In this study, the selection of models for both crime rates and clearance rates must occur before the dual trajectory links the trends over time. The first step is selecting the basic model depending on the type of data involved. The censored normal distribution (CNORM), the Poisson distribution, and the binary logit distribution are all forms of the basic model. A CNORM model is used for distribution of data that is in scales and where scores often cluster at one end of the scale. The Poisson distribution is used on count data, and the binary logit distribution is used when the outcome is binary. A CNORM model is most appropriate for both the clearance

¹⁹ Proc Traj is available at <https://www.andrew.cmu.edu/user/bjones/>. (See also Jones et al., 2001).

rate and crime rate data, as my data is not binary nor count data. The clearance and crime rate data best resembles scale data that is clustered towards the bottom. After selecting the model, the next step is determining the order of the model. The order can be linear, quadratic, or cubic. An order was selected for each crime type for each crime and clearance trajectory.

Next is the selection of the number of trajectory groupings. The groups are the trends of the data to compare to one another. The Bayesian information criterion (BIC) is used to select the number of groups, with the largest BIC score generally seen as the optimal choice (Nagin, 2005). The BIC is usually a negative number; therefore, the smallest negative number indicates the highest BIC score. However, occasionally it can also be a positive number, where the highest number indicates the highest BIC score. The equation of BIC measures how increasing parameters improves model fit but also creates a penalty in increasing complexity by adding more parameters. One potential problem with the BIC is that it may continue to increase with the addition of more groups by splitting larger groups into smaller groups (Nagin & Tremblay, 2001). In these instances, Nagin (2005) suggests selecting the model with the number of groups that best explains the data. The Akaike information criterion (AIC) is an alternative to using the BIC in model selection; however, because the equation does not include the sample size, it may favor models that add on additional yet non-meaningful groups (Nagin, 2005). Like the BIC, the optimal AIC increases, often as more groups are added. However, the AIC can be used in conjunction with the BIC as a guide to model selection. The BIC and AIC are

produced for each model for crime rates and clearance rates and used to help guide the selection of the optimal number of crime and clearance trajectory groupings.

Nagin (2005) also provides four steps to judge the accuracy of group membership assignment of the model. The first method is the average posterior probability (APP), which is the probability of individuals assigned to groups (with the highest probability being 1). Nagin suggests that the minimum APP for each group should be at least 0.7. The second method is the odds of correct classification (OCC), which measures whether groups have a high accuracy of assignment. Nagin suggests the OCC should be greater than 5.0 for all groups. The third method is the estimated probabilities versus the proportion of the sample assigned to the group. This is accomplished by examining the estimated group probability and proportion of individuals assigned based on the posterior probability. The fourth method is using confidence intervals for the group membership probabilities. Narrower confidence intervals are likely more accurate. These four steps judge each group within the selected trajectory model. I conducted these assessments on the final optimal crime rate and clearance rate models for each offense type, which demonstrates the fit of each trajectory group within the trajectory model.

Once these steps occur and the trajectory models for both crime rates and clearance rates selected, then the dual trajectory can be run. Three different probabilities are calculated in dual trajectory. These are the probability of membership in one trajectory conditional on membership in the other trajectory, the probability of the reverse membership in the opposite trajectory conditional on the other, and the probability of the linkage across the two measures. Therefore, there is a probability for membership in a

clearance rate trajectory given membership in a crime rate trajectory, a probability for membership in a crime rate trajectory given membership in a clearance rate trajectory, and a probability of joint membership in a crime rate and clearance rate trajectory. This joining of the trajectories is the advantage of the dual trajectory model over the single trajectory method (Nagin, 2005). The joining between the trajectories can either be a constrained model (linking each trajectory group in one model specifically with a trajectory group to the other model) or a general model (linkages of trajectories are not identified before analysis). I used the general model instead of making assumptions about the linkages of the trajectories before analysis. The general model describes the relationship between the linkages of crime rates and clearance rates in probabilistic terms, producing the three sets of probabilities as described above. I examined the period contemporaneously (examining how the crime rates and clearance rates occur together over time), and also lagged the period as well, linking the clearance rate to the crime rate of the next year, in order to see if there is evidence of a deterrent relationship. These probabilities will allow for a more complex relationship between the variables to emerge. Figure 5 shows the steps of dual trajectory analysis. These steps will occur for all four crimes in the analysis.

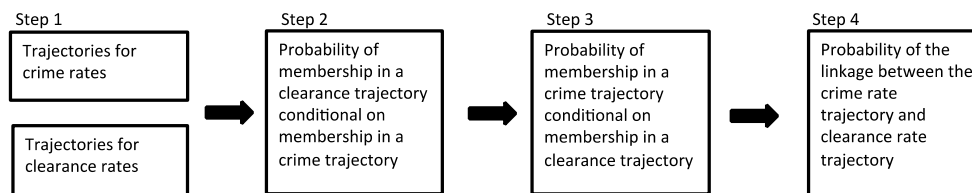


Figure 5. Steps of Trajectory and Dual Trajectory Analysis

The main limitation of trajectory analysis is that groups are an approximation (Nagin & Tremblay, 2001; 2005). Individual membership is not definite, nor is the number of groups. Individuals may develop differently over time, and not follow the trajectories in which they were placed (Nagin & Tremblay, 2005). It is possible that model selections may change with the addition of more cases, or more measures over time (Nagin & Tremblay, 2005). Even the use of model selection procedures such as the BIC and AIC is not definitively identifying a “correct” model (Nagin & Tremblay, 2001). Therefore, trajectory groups are not definitive, but an approximation based on the best available information.

Despite these limitations, dual trajectory analysis offers advantages over other longitudinal analyses seeking to link behaviors over time. Nagin (2005) describes how linking the probabilities of the measures across groups offer two advantages. The first is capturing how the trends overlap in the longitudinal relationship of the data. Second, the three probabilities produced by the dual trajectory offer several linkages that can better explain not only averages among the data but also deviations in the data as well.

Therefore, dual trajectory captures how the two different trends behave over time, as well as how these trends either occur or differ together.

In this study, trajectory analysis was run on both the created yearly clearance rate data for agencies as well as the crime rate data, to determine if trajectory groups were formed that placed agencies into groups that differ from the average trend. I conducted the trajectory analysis for both the clearance rates and crime rates using CNORM models for all crime types. I began with a 2-group linear, quadratic, or cubic parameter, and added groups until the BIC and AIC did not improve, the models did not converge, or the groups became too small (under 30 agencies). I adjusted the parameters to obtain the optimal shape of the trajectories. In addition to using the BIC and AIC as a guide, I also used the group diagnostics of assignment accuracy for the optimal trajectory model selection. Once I selected an optimal clearance rate model and crime rate model for each offense, I conducted the dual trajectory analysis. The dual trajectory analysis evaluated the selected crime rate and clearance rate trajectories by each offense and produced three sets of probabilities. The first is the probability of membership in the clearance rate trajectory given membership in the crime rate trajectory. The second probability is the probability of membership in the crime rate trajectory given membership in the clearance rate trajectory. The third probability is the joint probability of membership in a given crime rate and clearance rate trajectory. Overall, this analysis was undertaken to determine the type of relationship between crime rates and clearance rates in a large sample of police agencies with 100 or more authorized sworn officers: a negative relationship in which clearance rates increase while crime rates decrease, a relationship in

which crime rates and clearance rates increase (or decrease) together, or no relationship between crime and clearance rates.

CHAPTER FOUR: FINDINGS

This chapter presents the findings of the trajectory and dual trajectory analysis of the relationship between crime rates and clearance rates in homicide, robbery, aggravated assault, and burglary. Using the data as described in Chapter 3, this chapter presents the steps of the trajectory and dual trajectory process for each of the four offenses examined here. First, I conducted trajectory analysis to select an optimal clearance rate trajectory solution. I repeated single trajectory analysis to select an optimal crime rate trajectory solution. Once I had both an optimal clearance and crime rate trajectory solution for each offense, I performed the dual trajectory analysis, which produced the three probabilities of group membership.

To begin this process, I used the censored normal model (CNORM) for all solutions in both crime and clearance rates. The CNORM model is most appropriate for this data. The Poisson model uses count data, and my data contain rate calculations, not single counts of crime or clearance. The binary logit model was not appropriate, as the outcomes here are not binary. CNORM data works with scale data, which can be continuous or clustered at the minimum or maximum measures (Nagin, 2005). My data fits most closely to the clustered scale data.

The next step was selecting the ordering and number of groups for each solution. I first set ordering at 2-group linear, quadratic, or cubic parameters. I continued adding

groups while looking to see if the BIC and AIC continued to improve or stopped at an optimal solution. The BIC and AIC continued to improve, so I had to rely on other methods to help select the optimal model. I continued to add groups until it appeared that the groups split into non-meaningful groups, group memberships were extremely small (under 30 agencies), or the models no longer converged on a solution. Trajectory analysis is considered a finite mixture model, which assumes there is a finite number of groups in the population (Nagin, 2005). Solutions do not converge when the maximum likelihood estimator cannot estimate the parameters. After arriving at an optimal number of groups for the solution, I refined the order of the model to obtain the optimal shapes of the trajectories.

I selected models based on many criteria. While I used the BIC and AIC as a guide, these numbers often continuously improved as more groups were added. I was attentive to how the groups split as well as the number of agencies in each group. I also examined the model accuracy at estimating group membership probabilities of the trajectories. As discussed in Chapter 3, there are four criteria to judge the model accuracy. The first is the posterior probability of group membership (APP), which should be above 0.7 for each group. The second criteria is the odds of correct classification (OCC), which should be greater than 5. The third diagnostic is to examine whether the group's estimated probability ($\hat{\pi}$) is close to the proportion assigned to the group based on the maximum posterior probabilities (P_j). The final diagnostic is to determine whether the

95% confidence intervals for the estimated group membership probabilities are reasonably narrow.²⁰

Once I had the final solutions for clearance rates and crime rates for each offense, I could turn to the dual trajectory analysis. This involved running dual trajectory on the selected crime rate trajectory solution and clearance rate trajectory solution, which in turn produced three sets of probabilities. The first probability is the probability of membership in a clearance rate group given membership in a crime rate group. The second probability is the reverse – the probability of membership in a crime rate group conditional on membership in a clearance rate group. The final probability is the probability of belonging to a specific clearance rate group and a specific crime rate group. The results of these steps are presented below by offense.

Homicide Results

Between 1981 and 2013, homicide rates started at 11 homicides per 100,000 population, dropped to 8 homicides per 100,000 in the late 1980s, peaked at almost 12 homicides per 100,000 in 1993, and then dropped steadily to 7 homicides per 100,000 in 2013 (see Figure 4 in Chapter 3). Homicide clearances remained relatively steady, although slightly declining for this group of agencies (100 or more officers), from about 83% to around 78% (see Figure 2 in Chapter 3).

²⁰ Although Nagin (2005) uses 98% confidence intervals, the simulation and bootstrapping method to obtain these numbers is complex and time-consuming. Discussion with committee members indicated that the calculation of 95% confidence intervals is acceptable. I calculated the 95% confidence intervals using the estimated group membership probabilities coefficient and their standard error.

Homicide Clearance Rate Trajectories

Homicides are often rare crimes, especially among smaller agencies, so the clearance rate varied widely.²¹ Due to the widespread and non-normal distribution of the homicide data, the trajectory analysis had difficulty converging. The maximum clearance rate value in the sample was 10. Although I considered truncation, I decided to set the maximum value at 100, ten times the maximum clearance rate value. This changes the way that the maximum likelihood procedure searches the CNORM model for the distribution without changing the data.²² The models then converged after I changed the maximum value to 100.

The final sample size for the homicide clearance data is 519 agencies. Following the steps above for the model search, I selected a 3-group solution (order 2 2 1) as the final model. The 3-group solution offered an improvement of the BIC and AIC from the 2-group model and produced a new group. Although the BIC and AIC slightly improved for the 4-group solution, one of the trajectory groups contained only eight agencies, too small to be a meaningful group. The BIC for the 3-group model is -5397.82, and the AIC is -5374.43.

Additionally, I checked the model fit diagnostics for the 3-group solution. Table 3 presents these findings. APP represents the posterior probability; OCC is the odds of correct classification. The estimated probability of assignment for each group is represented by $\hat{\pi}$. P_j represents the proportion of the sample classified in a given group.

²¹ The minimum value in the data was 0.01, the maximum value was 10.00, and the overall mean was 0.79.

²² Increasing the maximum value allows the maximum likelihood estimator to identify the parameters that maximize the likelihood function. Discussion with trajectory analysis experts indicated that this was a suitable method to get the models to converge.

The 95% confidence intervals for the estimated probability of group membership ($\hat{\pi}$) portray the lower and upper 95% confidence intervals (C.I.). This table shows that the assignment of groups performed well. The APP is above the 0.7 threshold for each group, the OCC for each group is above 5, and the correspondence between the estimated probabilities of assignment versus the proportion of sample assigned to each group is close. While there is no exact cut-off to determine the narrowness of confidence intervals, the 95% confidence intervals here for all groups' estimated membership probabilities are reasonably narrow.

Table 3. Homicide Clearance Trajectory Group Diagnostics of Assignment Accuracy

Group	$\hat{\pi}$	Ave. PP	OCC	P_j	95% C.I. for $\hat{\pi}$
Low Decreasers	0.16	0.90	47.25	0.15	0.11, 0.20
High Decreasers	0.53	0.89	7.17	0.54	0.46, 0.59
High Increaseers	0.32	0.88	15.58	0.31	0.24, 0.40

The results of the 3-group solution indicate variations in the average trend (see Figure 6). The first group, the low decreaseers (about 16% of the sample), start at almost 70% clearance rate and decline to about 50%. This group is below the average trend of the sample. The high decreaseers are the second group, consisting of 53% of the sample and follow the average trend. This group has a clearance rate beginning at 85% and dropping to around 75%. This group is performing better than the mean clearance rate trend but is still declining in their ability to clear crime. The final group is improving over

the average trend. This group, the high increasers (32% of agencies), starts around 85% clearance and improves to nearly 100% clearance rate.

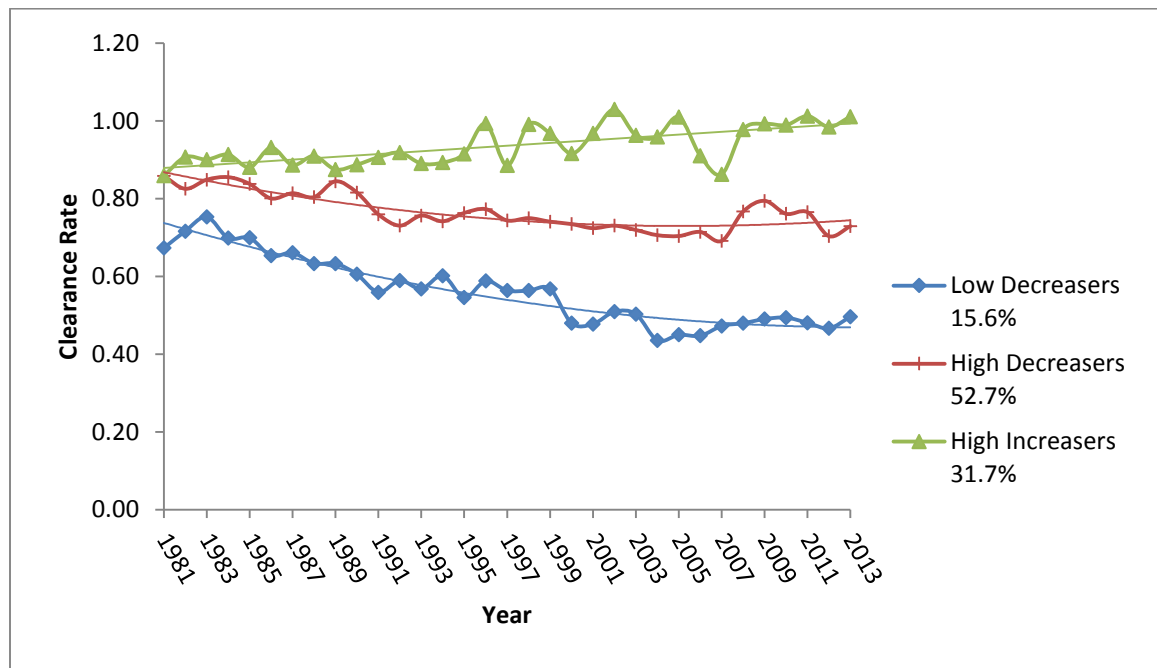


Figure 6. Homicide Clearance Rate 3-Group Trajectory Solution (n=519)

Homicide Crime Rate Trajectories

I calculated the homicide crime rate data by the number of offenses divided by the population, which was then multiplied by 100,000. This calculation converged upon solutions of up to 5 groups. After completing the model search and examining the model selection criteria, I picked a 2-group (order 1 3) trajectory model. Although the BIC continued to improve as more groups were added, the addition of new groups dropped at least one group size in each model under 30 agencies. The BIC for the 2-group crime rate model is -55329.34, and the AIC is -55312.33.

The diagnostics for model accuracy performed well for each group. Table 4 presents the homicide crime rate 2-group diagnostics. The APP is nearly 1 for each group, the OCC is above 5 for the two groups, and the estimated group probabilities versus the proportion of the sample assigned to a group are identical. The 95% confidence intervals for each group's estimated membership probabilities are narrow.

Table 4. Homicide Crime Rate Trajectory Group Diagnostics of Assignment Accuracy

Group	$\hat{\pi}$	Ave. PP	OCC	P_j	95% C.I. for $\hat{\pi}$
Low Stable	0.90	0.99	11.00	0.90	0.87, 0.93
High Increase then Stable	0.10	0.99	891.00	0.10	0.08, 0.13

The trajectory findings indicate there is a variation from the average trend in the crime rate data (see Figure 7). The first group consists of the majority of the agencies (90%). This group, the low stable trajectory, is similar to the average trend. This group begins with a crime rate of nine homicides per 100,000 population and slightly declines to about five homicides per 100,000 population. However, the second group starts with a crime rate around 28 homicides per 100,000, peaks at above 35 per 100,000 in 1993, then declines and stabilizes to just above 20 homicides per 100,000 population at the end. This group, the high increasers then stable group, accounts for 10% of the agencies and has a higher crime rate than the sample average.

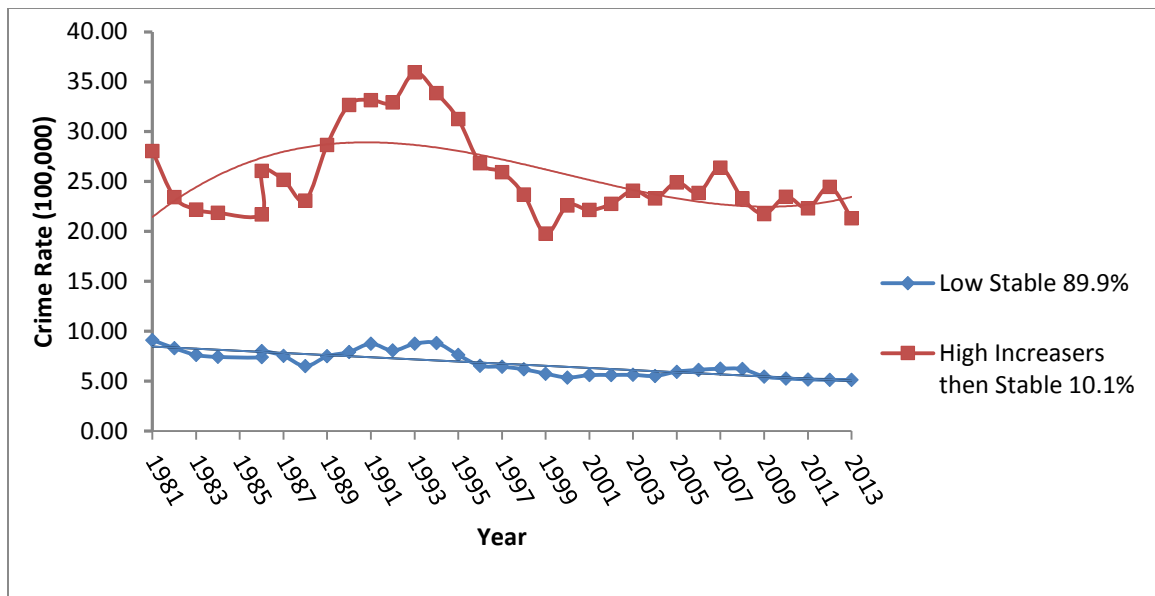


Figure 7. Homicide Crime Rate 2-Group Trajectory Solution (n=519)

Dual Trajectory of Homicide Crime Rates and Clearance Rates

The dual trajectory model can either be a constrained model or a general model.

The constrained model links trajectories in one model specifically to trajectories in another model, whereas the general model does not make these assumptions before analysis. I used the general model in the following analyses. Instead of making assumptions about the linkages, the probabilities can characterize the linkages (Nagin, 2005). Dual trajectory analysis offers three probability representations: the probability of membership in one trajectory conditional on membership in the other trajectory, the probability of the reverse membership in the opposite trajectory conditional on the other, and the probability of the linkage across the two measures. The three probabilities describe how linkages occur across the measured period. The two conditional probabilities demonstrate how the trajectories of one model (for example, clearance rate

trajectories) are related to the trajectories of another model (the crime rate trajectories).

The joint probability linkage gives the probability of linking one clearance trajectory to a crime rate trajectory. The three probabilities are used to capture the behaviors of the trajectories, but it does not resolve causality in the relationship.

The following three tables display the results of the dual trajectory analysis for homicide. For these displays, the first table indicates the probability of membership in the crime trajectory conditional on the probability of membership in the clearance rate trajectory. Here, each column of probabilities sums to 1. The second table shows the probability of membership in the clearance rate group conditional on the probability of membership in the crime rate trajectory. The probabilities of each row sum to 1. The third table presents the joint probability of belonging to a specific crime rate and clearance rate group. The entire table of probabilities sums to 1.²³

Table 5 displays the probability of membership in a crime rate group conditional on the clearance rate group membership. The table demonstrates that agencies with a high increasing clearance rate always (100%) have a low stable homicide rate. Agencies with a high decreasing clearance rate also have an extremely high probability (96%) of falling into the low stable homicide rate trajectory. Even agencies with a low decreasing clearance rate have a slightly higher likelihood of following the low stable homicide rate (58% probability) as compared to the higher homicide rate (42% probability). These results indicate that agencies with high clearance rates – both increasing and decreasing – are most likely to have a low stable homicide rate.

²³ The presentation of the three tables and their probabilities apply to each offense and dual trajectory analyses tables discussed below.

Table 5. Homicide Probability of Crime Rate Group Conditional on Clearance Rate Group

Crime Rate Group	Clearance Rate Group		
	Low Decreasers	High Decreasers	High Increases
Low Stable	0.58	0.94	1.00
High Increases then Stable	0.42	0.06	0.00

Table 6 shows the probability of membership in a clearance rate group conditional on the crime rate. These results also show a relationship between crime rates and clearance rates. Agencies with a high increasing then stable homicide rate have a 68% probability of following the low decreasing clearance trajectory and have zero probability to be in a high increasing clearance trajectory. However, a low stable homicide rate has a 53% likelihood of placement in a high decreasing clearance trajectory, and 36% chance of following the high increasing clearance trajectory. This table indicates that agencies with a higher crime rate are more likely to be in the lowest clearance rate group, while agencies with a lower crime rate tend to follow higher clearance patterns – both decreasing and increasing.

Table 6. Homicide Probability of Clearance Rate Group Conditional on Crime Rate Group

Crime Rate Group	Clearance Rate Group		
	Low Decreasers	High Decreasers	High Increases
Low Stable	0.11	0.53	0.36
High Increases then Stable	0.68	0.32	0.00

Finally, Table 7 presents the joint probability of membership in a clearance rate group and crime rate group. Probabilities across all cells sum to 1. The findings confirm the previous two demonstrations. The probability for agencies with a low stable homicide rate and a high decreasing clearance rate is 48%, which is the most common case among all possible combinations. Agencies have a 33% likelihood of placement in a high increasing clearance trajectory and a low stable homicide rate. In fact, there is zero probability of belonging to a high homicide rate group and high increasing clearance rate group. Overall, the dual trajectory findings indicate that agencies with a low stable homicide rate tend to have higher clearances. This relationship appears with both high increasing and high decreasing clearances, so there is still some variation here between low homicide rates and clearance rate performance. However, those agencies with a high homicide rate tend to perform worse in their clearances.

Table 7. Homicide Joint Probability of Clearance Rate Group and Crime Rate Group

Crime Rate Group	Clearance Rate Group		
	Low Decreasers	High Decreasers	High Increases
Low Stable	0.09	0.48	0.33
High Increases then Stable	0.07	0.03	0.00

Robbery Results

Between 1981-2013, the robbery crime rate fluctuates slightly (see Figure 3 in Chapter 3). The robbery crime rate starts at 200 robberies per 100,000 population, increases slightly over 200 robberies per 100,000 and falls to under 150 robberies per

100,000. The robbery clearance rate for this sample has increased very slightly, beginning around 30% in 1981 and ending at near 37% in 2013 (see Figure 2 in Chapter 3).

Robbery Clearance Rate Trajectories

The optimal trajectory solution for the robbery clearance rate data is a 5-group solution (order 2 2 1 1 2). Although the BIC and AIC improved with a 6-group solution, it split the top trajectory into two similar groups. The 5-group solution offered a higher BIC and AIC as well as a new group over the 4-group solution. The BIC for the 5-group is 11561.81, and the AIC is 11603.21. The final sample size for the robbery clearance rate trajectory is 729.

The model accuracy diagnostics indicate the model performed well in estimating group membership. Table 8 presents the robbery clearance trajectories diagnostics. The APP is 0.91 or above for each group. The OCC is well above 5 for all groups. The correspondence between the estimated group membership probabilities versus the proportion of the group assigned to the sample is very close. The 95% confidence intervals for each group's estimated membership probabilities are reasonably narrow.

Table 8. Robbery Clearance Trajectory Group Diagnostics of Assignment Accuracy

Group	$\hat{\pi}$	Ave. PP	OCC	P_j	95% C.I. for $\hat{\pi}$
Low Stable	0.22	0.92	40.77	0.22	0.18, 0.25
Low Slight Increasers	0.36	0.92	20.44	0.35	0.30, 0.41
Middle Decreasers	0.19	0.91	43.11	0.19	0.15, 0.22
Middle Increasers	0.17	0.94	76.49	0.17	0.14, 0.20
High Slight Decreasers	0.07	0.97	429.57	0.08	0.05, 0.09

Figure 8 presents the robbery clearance rate trajectories. The average clearance rate for the sample was around 30% clearance and increasing slightly over time. These results show variation from that average. The first group, the low stable group at about 22% of the sample, performs slightly worse than the average, beginning at 25% clearance and decreasing slightly to around 20%. The low slight increasers most closely mirror the national sample, starting at 30% clearance and increasing slightly over time. This group accounts for nearly 36% of the sample. The middle decreasers consist of 19% of the agencies, and begin at 45% clearance but drop to the average, around 30% clearance. The middle increasers begin at 30% clearance but end up performing much better than the mean clearance rate, ending at 50% clearance. This group accounts for 17% of the agencies. Finally, the high slight decreasers have an extremely high clearance rate, which decreases slightly over time, but is still well above the average (beginning at 53% clearance and ending around 50%). This group contains about 8% of the agencies.

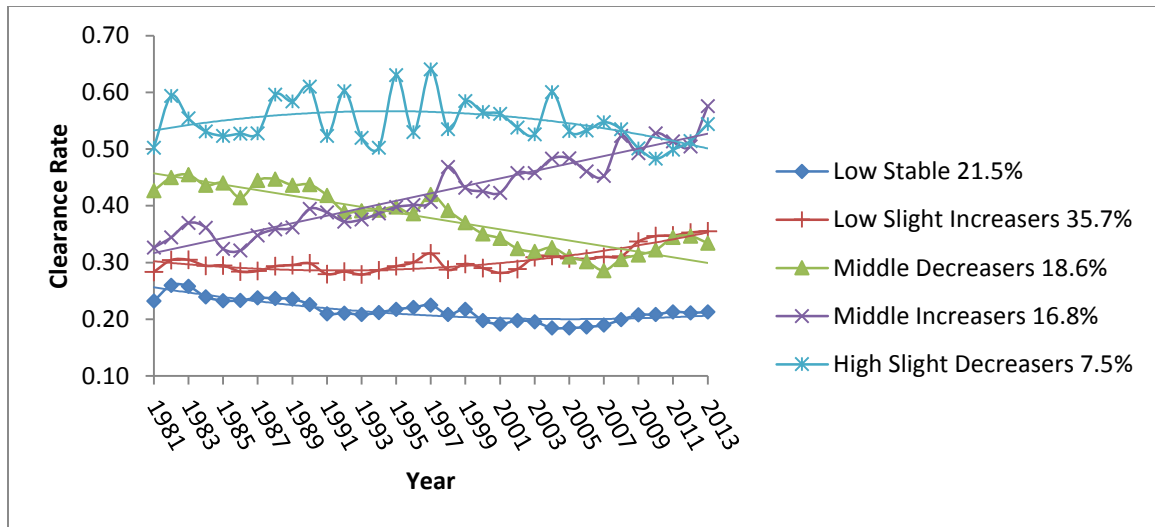


Figure 8. Robbery Clearance Rate 5-Group Trajectory Solution (n=729)

Robbery Crime Rate Trajectories

The robbery crime rate data would not converge with the crime rate calculation set to 100,000 due to the non-normal dispersion of the data²⁴ and the widespread minimum and maximum values.²⁵ I changed the crime rate calculation to 1,000 population, which also would not converge. Finally, I changed it to 100, which did converge. Therefore, the final crime rate calculation for robbery is the number of offenses divided by population multiplied by 100.

I selected a 3-group model (order 1 2 2) as the optimal model. It offered an improvement in the BIC and AIC over the 2-group solution, as well as a new group. Although the 4-group model had a higher BIC and AIC, one of the trajectory groups contained only 20 agencies. The BIC is 15882.26, and the AIC is 15907.81. The final sample size for the robbery crime rate is 728.

²⁴ The crime rate data for all four crimes skewed left.

²⁵ The minimum for the robbery crime rate data was 0, the maximum was 2,340, and the average was 187.97.

Table 9 presents the diagnostics of the model fit for the robbery crime rate trajectories. This chart demonstrates that the model performed well when estimating the group membership probabilities. The APP is nearly 1 for each group, the OCC is well above 5 for every group, and the estimated group probabilities versus the proportion of the sample assigned to a group is identical. The 95% confidence intervals for the estimated group membership of each group are narrow.

Table 9. Robbery Crime Rate Trajectory Group Diagnostics of Assignment Accuracy

Group	$\hat{\pi}$	Ave. PP	OCC	P_j	95% C.I. for $\hat{\pi}$
Low Stable	0.70	0.99	42.43	0.70	0.67, 0.73
Middle Slight Decreasers	0.23	0.99	331.43	0.23	0.20, 0.26
High Decreasers	0.07	0.99	1315.29	0.07	0.05, 0.09

Figure 9 presents the robbery crime rate trajectory results.²⁶ The average crime rate of the sample was about 250 robberies per 100,000, dropping to under 150 per 100,000. The first group is the low stable group with 70% of the agencies. Their crime rate is stable at 100 robberies per 100,000 population throughout the period. The low stable group has a lower crime rate than the average, although the average does decrease to similar rates at the end of the period. 23% of agencies belong to the middle stable trajectory, with a crime rate above 300 per 100,000, which fluctuates and drops to around 250 robberies per 100,000 population. The middle stable trajectory has a slightly higher

²⁶ Although the robbery crime rate trajectory analysis was conducted with the crime rate calculated per 100 population, I am presenting these results, as well as the assault and burglary crime rate results, in the 100,000 population. This allows for uniformity in discussing crime rates among all offenses here. I plugged in the original 100,000 data and created charts that were identical to the trajectories with the 100 per population rate calculation.

crime rate than the average but follows a similar pattern. The final group, the high decreaseers, experiences a dramatic drop in their crime rate and have a much higher crime rate than the average. They begin at 950 robberies per 100,000 and drop to nearly 500 robberies per 100,000 population. This group consists of nearly 7% of the agencies.

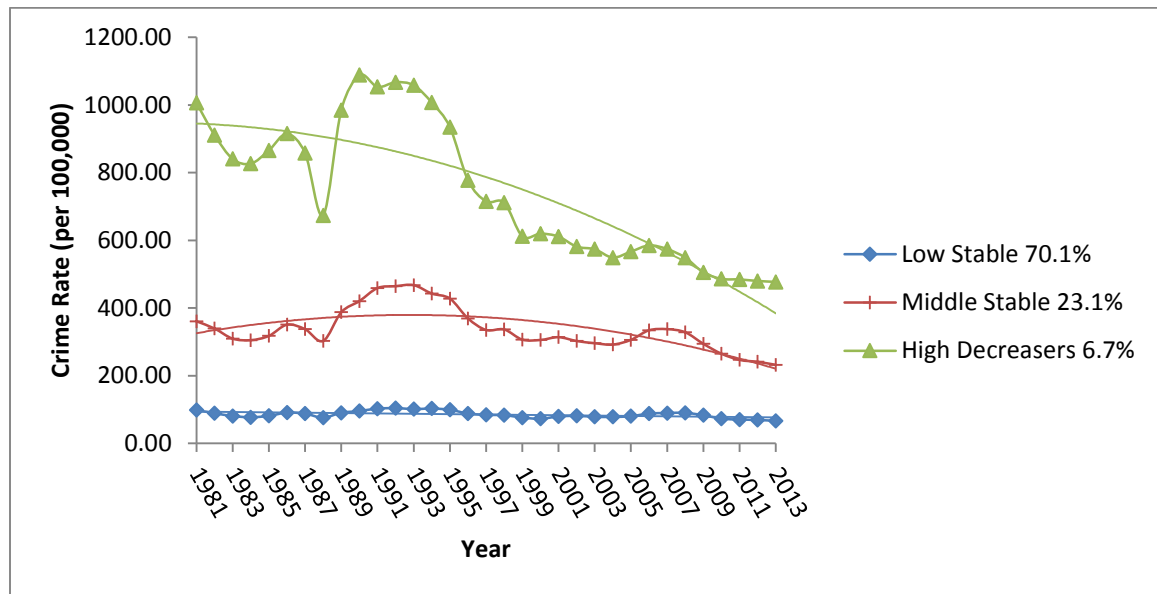


Figure 9. Robbery Crime Rate 3-Group Trajectory Solution (n=728)

Dual Trajectory of Robbery Crime Rates and Clearance Rates

The next three tables present the dual trajectory results. Table 10 demonstrates the probability of belonging to a crime rate trajectory based on membership in a clearance rate trajectory. Here, all clearance rate trajectories are more likely to belong to the low crime rate trajectory. Agencies with a high, though slightly decreasing clearance rate have a 100% probability of falling into the low stable robbery group. There is a 96% likelihood for agencies with a middle increasing

clearance rate trajectory to follow the low stable robbery rate. The middle decreasing clearance rate has an 84% chance of following the low robbery rate, while the low slight increasers have a 69% probability of belonging to the low stable robbery rate. The highest probability for the lowest clearance rate is a 44% chance of following the middle decreasing robbery rate. The results from this panel indicate a consistent relationship between low robbery rates and higher clearance rates. However, as clearance rates decline, the chance of belonging to a low stable robbery rate decrease as well.

Table 10. Robbery Probability of Crime Rate Group Conditional on Clearance Rate Group

Crime Rate Group	Clearance Rate Group				
	Low Stable	Low Slight Increasers	Middle Decreasers	Middle Increasers	High Slight Decreasers
Low Stable	0.31	0.69	0.84	0.96	1.00
Middle Slight Decreasers	0.44	0.28	0.16	0.03	0.00
High Decreasers	0.24	0.03	0.00	0.01	0.00

Table 11 presents the results of membership in a clearance rate trajectory given membership in a crime rate trajectory. Agencies with a high robbery rate have an 80% probability of placement into the low stable clearance rate trajectory. A middle robbery rate has a 43% probability of following the low slightly increasing clearance trajectory or a 42% likelihood of placement into the low stable clearance rate group. The low stable robbery rate has a 35% probability of following the low increasing clearance trajectory. This table shows that agencies with a higher crime rate tend to have a low clearance rate..

Table 11. Robbery Probability of Clearance Rate Group Conditional on Crime Rate Group

Crime Rate Group	Clearance Rate Group				
	Low Stable	Low Slight Increases	Middle Decreasers	Middle Increases	High Slight Decreasers
Low Stable	0.10	0.35	0.22	0.23	0.11
Middle Slight Decreasers	0.42	0.43	0.13	0.03	0.00
High Decreasers	0.80	0.18	0.00	0.02	0.00

Finally, Table 12 presents the joint probability of membership in a clearance rate and crime rate trajectory. The highest probability is a 24% probability of membership in a low stable robbery rate and low increasing clearance rate trajectory. Agencies have a 16% probability of placement in a low robbery rate and a middle increasing clearance trajectory, or 15% in the low robbery rate and middle decreasing clearance trajectory. The robbery results indicate that agencies that have a low robbery rate tend to show low increasing to middle clearances, whether increasing or decreasing over time. Agencies with a higher robbery rate have a lower clearance rate, both stable and increasing over time. There appears to be variability in how low robbery rate agencies perform in their clearances – both increasing and decreasing over time.

Table 12. Robbery Joint Probability of Clearance Rate Group and Crime Rate Group

Crime Rate Group	Clearance Rate Group				
	Low Stable	Low Slight Increases	Middle Decreasers	Middle Increases	High Slight Decreasers
Low Stable	0.07	0.24	0.15	0.16	0.08
Middle Slight Decreasers	0.10	0.10	0.03	0.01	0.00
High Decreasers	0.05	0.01	0.00	0.00	0.00

Aggravated Assault Results

The aggravated assault crime rate for the sample has fluctuated slightly over time (see Figure 3 in Chapter 3). Aggravated assault begins with a crime rate of 300 assaults per 100,000 in 1981, slightly increases to over 400 assaults in the early 1990s, and ends close to 250 assaults per 100,000 population in 2013. The aggravated assault clearance rate has remained relatively stable, beginning and ending at 60% (see Figure 2 in Chapter 3).

Aggravated Assault Clearance Rate Trajectories

The optimal trajectory solution for the assault clearance data is a 6-group (order 2 1 2 2 2 1) solution. Although a 7-group model did produce a lower BIC/AIC, it split the second and third trajectories into a similar one. The 6-group solution produced a new trajectory (trajectory group 3) that was not in the 5-group model. The 6-group solution has a BIC of 9220.62, and the AIC is 9270.25. The final sample size for the aggravated assault clearance data is 673.

Table 13 presents the diagnostics for group membership. These numbers show the model performed well at predicting group membership. The APP is 0.92 or above for each group, the OCC is well above 5.0, and the estimated group membership probabilities versus the proportion of the sample assigned to the group closely corresponds. The 95% confidence intervals for each group's estimated membership probabilities are narrow.

Table 13. Aggravated Assault Clearance Trajectory Group Diagnostics of Assignment Accuracy

Group	$\hat{\pi}$	Ave. PP	OCC	P_j	95% C.I. for $\hat{\pi}$
Low Recoverers	0.10	0.96	216.00	0.10	0.08, 0.12
Low Increases	0.17	0.95	92.76	0.17	0.14, 0.20
Middle Increases	0.16	0.92	60.38	0.16	0.12, 0.19
Middle Decreasers	0.20	0.93	53.14	0.20	0.16, 0.24
High Decreasers	0.27	0.94	42.36	0.26	0.22, 0.31
Very High Slight Decreasers	0.10	0.94	141.00	0.10	0.07, 0.13

Figure 10 presents the clearance rate trajectory model. There is considerable variation in clearance rates from the average in these trajectories. The average clearance rate is relatively stable at around 60% clearance. Here, no trajectory follows that exact path. The first trajectory group consists of 10% of the sample. These agencies are the low recoverers and well below the average, starting with a clearance rate of 40%, decreasing to fewer than 40%, and ending again at above 40%. Low increasers, the second trajectory group, consist of 17% of agencies. They demonstrate a substantial increase in clearance, starting below the average of 40% and increasing to almost 70%. The third group, the mid increasers, contains 16% of agencies and begins at the average of 60% clearance rate and improves to around 75%. The fourth group is the mid decreasers, starting at 70% clearance rate but dropping to under 50%. This fourth group contains 20% of agencies. The fifth group, the high decreasers, consists of 27% of agencies. They begin above the average at 80% clearance but drop to the average of 60%. 10% of agencies are in the sixth group, which are the very high slight decreasers. They are well above the average, starting at 85% clearance but end around 80%.

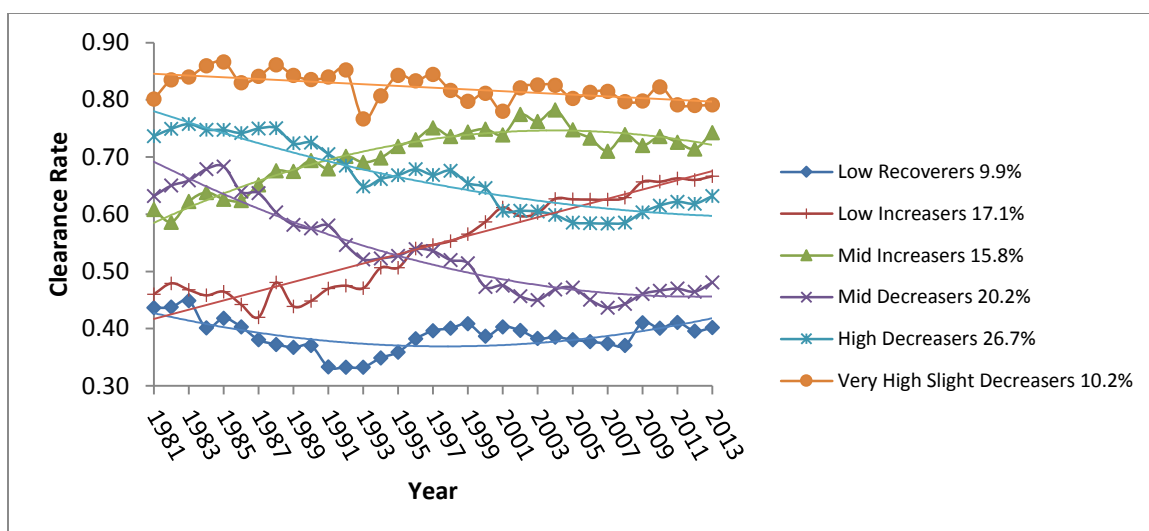


Figure 10. Aggravated Assault Clearance Rate 6-Group Trajectory Solution (n=673)

Aggravated Assault Crime Rate Trajectories

As with the robbery data, the assault crime rate data would not converge with a crime rate calculation of 100,000.²⁷ I tried a calculation of the crime rate set to 1,000 and 100, which also would not converge. I decided to take the square root of the crime rate (per 100,000), as it allowed for 0's in the data and best modeled the original data.²⁸ The final solution is a 4-group model (order 1 2 2 3). The BIC and AIC continued to improve with the addition of each new group. At five groups, one of the groups contained fewer than 30 agencies. Therefore, the 4-group model was selected. The 4-group model has a BIC of -65883.36, and AIC of -65847.33.

²⁷ Again, the assault crime rate data was skewed to the left with a minimum of 0, maximum value of 5101.54, and mean of 336.87.

²⁸ Discussion with members of the committee suggested both logging the values as well as the square root option. However, logging does not work on zero values, so I set zeros to 0.5. I graphed the original 100,000 crime rate calculation for each year, the average logged values, and the average square root values. I picked the square root because it best followed the original data trends.

Table 14 present the model fit diagnostics. The assault crime rate 4-group trajectories performed well by the model fit diagnostics criteria. The APP is close to 1 for all groups, the OCC is well above 5, and the estimated group membership probabilities is the same as the proportion of the sample assigned to the group. The 95% confidence intervals for the estimated group membership probabilities are narrow for each group.

Table 14. Aggravated Assault Crime Rate Trajectory Group Diagnostics of Assignment Accuracy

Group	$\hat{\pi}$	Ave. PP	OCC	P_j	95% C.I. for $\hat{\pi}$
Low Stable	0.27	0.99	267.67	0.27	0.24, 0.31
Middle Stable	0.35	0.98	91.00	0.35	0.31, 0.38
Mid-High Stable	0.28	0.98	126.00	0.28	0.25, 0.32
High Increases then Decreasers	0.10	0.99	891.00	0.10	0.08, 0.12

Figure 11 presents the crime rate results.²⁹ The average crime rate was close to 300 assaults per 100,000 falling to around 250 assaults per 100,000. The first trajectory group consists of 27% of the sample. These agencies are low stable and lower than the average crime rate, with the crime rate around 100 assaults per 100,000 population from the beginning to end of the period. The second trajectory group, the mid-stable group, consists of nearly 35% of agencies. They remain relatively stable throughout the period with a crime rate around 200 assaults per 100,000. The mid-stable group is slightly below the average but follows a similar pattern. The third group is the high-mid stable that begins at a crime rate of 400 assaults per 100,000, increases slightly and ends back around 400 assaults per 100,000. This group consists of 28% of the agencies and contains

²⁹ The original 100,000 crime rate calculation is presented here instead of the square root numbers.

a slightly higher crime rate than the average but displays a similar trend. The final group is the high increasers then decreasers at 10% of the agencies. This group has a crime rate around 600 assaults per 100,000 population, increases to around 1,200 assaults, but drops again to around 600 assaults per 100,000. This group is well above the average of the sample.

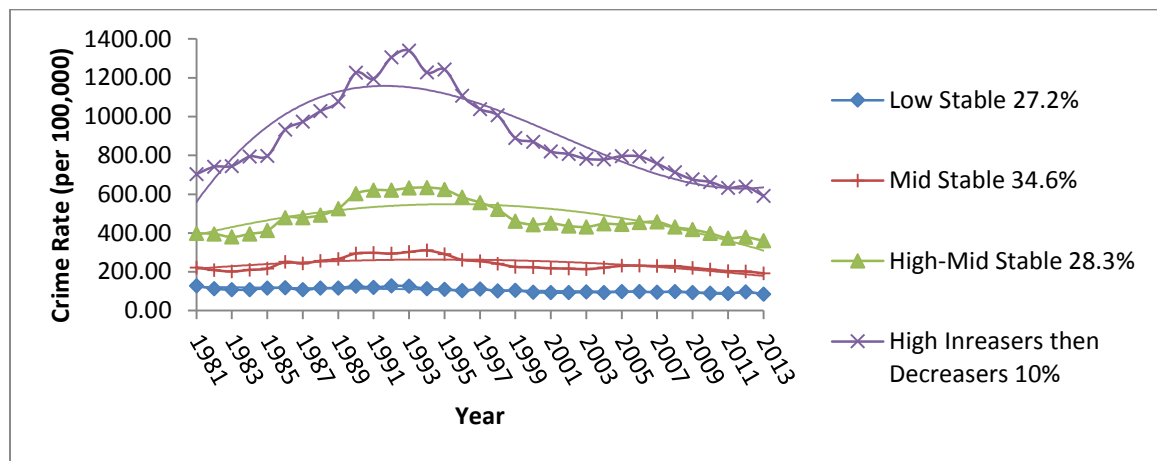


Figure 11. Aggravated Assault Crime Rate 4-Group Trajectory Solution (n=668)

Dual Trajectory of Aggravated Assault Crime Rates and Clearance Rates

The following three tables present the aggravated assault dual trajectory results.

Table 15 presents the results of the probability of membership in a crime trajectory conditional on the clearance rate group. Agencies with a very high and slightly decreasing clearance rate have a 64% probability of following a low assault rate trajectory. A low increasing or middle increasing clearance rate is likely to follow the mid stable assault rate group (44% and 40% probability respectively). There is a 42% likelihood of agencies with a middle decreasing clearance trajectory to follow a high-mid

stable assault rate. This table demonstrates that agencies with a very high clearance rate fall into the lowest assault rate group, while the two increasing clearance trajectories are most likely to follow a low or middle stable assault rate group.

Table 15. Aggravated Assault Probability of Crime Rate Group Conditional on Clearance Rate Group

Crime Rate Group	Clearance Rate Group					
	Low Recoverers	Low Increases	Mid Increases	Mid Decreases	High Decreases	Very High Slight Decreases
Low Stable	0.12	0.27	0.39	0.10	0.26	0.64
Mid Stable	0.22	0.44	0.40	0.28	0.35	0.31
High-Mid Stable	0.38	0.24	0.16	0.42	0.34	0.05
High Increases then Decreases	0.28	0.05	0.05	0.20	0.06	0.00

Table 16 shows the probability of membership in the clearance rate trajectory conditional on the crime trajectory. There is a 41% probability for agencies with a high assault rate to follow a middle decreasing clearance trajectory. Agencies with a high-mid stable crime rate are most likely to belong to the middle decreasing (30% probability) or high decreasing (32% probability) clearance trajectories. Agencies with a low assault rate tend to belong to the two high decreasing clearance trajectories (25% probability in the high decreasing clearance group and 24% in the very high decreasing clearance trajectory) or the middle increasing clearance trajectory (24% probability). Here, agencies with higher crime rates tend to belong to declining clearance trajectories, indicating a decrease in clearances over time. A low assault rate indicates the greatest probability in

the two highest, though decreasing clearance trajectories, and the middle increasing trajectory.

Table 16. Aggravated Assault Probability of Clearance Rate Group Conditional on Crime Rate Group

Crime Rate Group	Clearance Rate Group					
	Low Recoverers	Low Increases	Mid Increases	Mid Decreases	High Decreases	Very High Slight Decreases
Low Stable	0.04	0.16	0.24	0.07	0.25	0.24
Mid Stable	0.07	0.21	0.20	0.17	0.27	0.09
High-Mid Stable	0.14	0.14	0.09	0.30	0.32	0.02
High Increases then Decreases	0.28	0.09	0.09	0.41	0.15	0.00

Table 17 presents the joint probability of membership in both a crime rate and clearance rate group. The greatest probability is 9% likelihood for agencies to belong to a mid-stable assault rate group and a high decreasing clearance trajectory. Agencies also have a 9% probability of belonging to the high mid stable assault rate trajectory and the high decreasing clearance trajectory. Agencies have an 8% probability of belonging to a high decreasing clearance trajectory and a high-mid stable assault rate group. There is an equal probability of 7% for agencies to be in a low stable assault rate group and either a middle increasing clearance or high decreasing clearance trajectory.

These results demonstrate variation in clearance performance and crime rate levels. The probabilities are fairly evenly spread out, indicating no clear pattern between crime rates and clearance rates. Agencies with a low assault rate are most liable to belong

to a high performing, though decreasing, clearance trajectory, but also the middle increasing clearance trajectory. A high assault rate is most probable to contain agencies with a low or declining clearance performance. The middle two assault rate groups contain agencies with middle improving to high decreasing trajectories.

Table 17. Aggravated Assault Joint Probability of Clearance Rate Group and Crime Rate Group

Crime Rate Group	Clearance Rate Group					
	Low Recoverers	Low Increases	Mid Increases	Mid Decreasers	High Decreasers	Very High Slight Decreasers
Low Stable	0.01	0.04	0.07	0.02	0.07	0.06
Mid Stable	0.02	0.07	0.07	0.06	0.09	0.03
High-Mid Stable	0.04	0.04	0.03	0.08	0.09	0.01
High Increases then Decreasers	0.03	0.01	0.01	0.04	0.02	0.00

Burglary Results

Between 1981 and 2013, the burglary crime rate for the sample has steadily decreased (see Figure 3 in Chapter 3). The average burglary crime rate begins at over 1,800 burglaries per 100,000 population in 1981 and falls to near 700 burglaries per 100,000 in 2013. The sample's clearance rate has remained relatively stable, near 15% (see Figure 2 in Chapter 3).

Burglary Clearance Rate Trajectories

The optimal burglary clearance rate solution is a 4-group (order 1 1 1 2) model. Although the BIC and AIC continued to improve as more groups were added, the 5-group

solution contained one trajectory group under 30. The 4-group solution offered an increasing trajectory group that was not in the 3-group model; therefore, the 4-group model was selected as the optimal solution. The BIC is 28576.60, and the AIC is 28606.39.

Table 18 shows the diagnostics of the model accuracy of the group assignment for the burglary clearance trajectories. These numbers show the model performed well at estimating group assignment. The APP is 0.95 and above for each group, the OCC is well above 5 for every group, and the estimated probabilities of group assignment correspond to the proportion of the sample assigned to the group. The 95% confidence intervals for estimated membership probabilities are narrow for each group.

Table 18. Burglary Clearance Trajectory Group Diagnostics of Assignment Accuracy

Group	π	Ave. PP	OCC	P_j	95% C.I. for π
Low Stable	0.55	0.98	40.09	0.55	0.51, 0.58
Low Increasers	0.27	0.95	51.37	0.27	0.23, 0.30
High Decreasers	0.14	0.95	116.71	0.14	0.11, 0.17
High Increasers then Decreasers	0.05	0.98	931.00	0.05	0.03, 0.06

Figure 12 presents the burglary clearance rate trajectory solution. The first trajectory group is the low stable clearance group, consisting of almost 55% of the population. This group mirrors the average with a clearance rate around 12% that decreases very slightly over time. The second group, the low increasers, starts slightly better than the mean at 16% clearance and improves to around 20%. This group consists

of nearly 27% of the agencies. The third group is the high decreasers (14% of agencies). They begin with a high clearance rate of 28% but drop to the average (around 13%) at the end. The final group contains about 5% of the agencies. They begin at 25% clearance; improve to over 30%, but drop back to 25% clearance. The results of this trajectory analysis demonstrate variations from the average 15% burglary clearance rate.

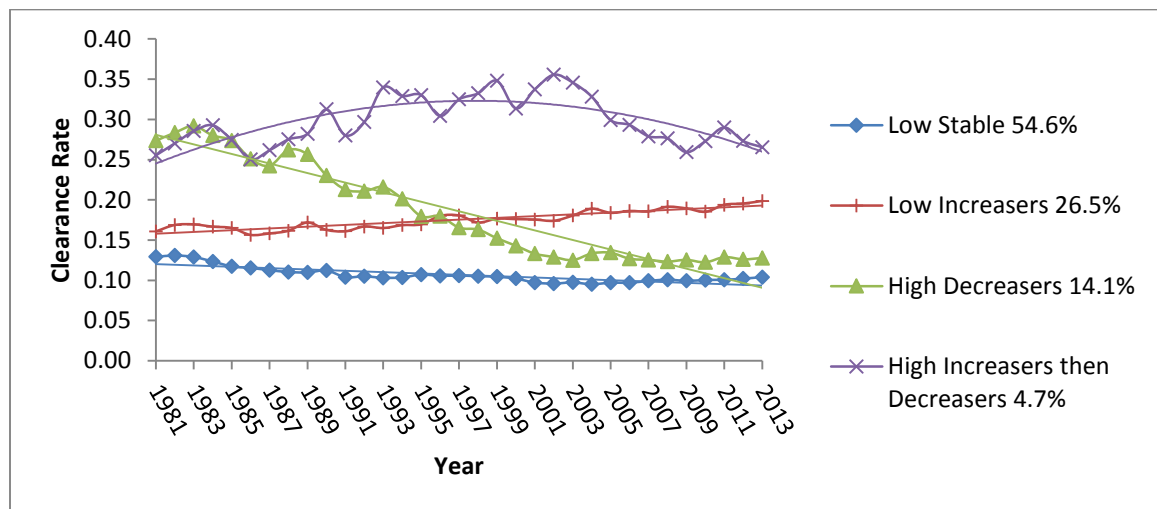


Figure 12. Burglary Clearance Rate 4-Group Trajectory Solution (n=757)

Burglary Crime Rate Trajectories

Similar to the issue with the robbery crime rate, the burglary crime rate would not converge at a calculation of 100,000 or 1,000.³⁰ The models converged when the crime rate calculation was set to a rate of 100. The optimal model selected is a 4-group (order 2 2 3 3) solution. Once again, the BIC and AIC improved with more groups added, but the 5-group solution produced a trajectory with only 17 agencies. I selected the 4-group

³⁰ The data was once again skewed left, with a minimum of 0, a maximum of 9,895.43, and mean of 1,136.20.

model over the 3-group model because of the improved BIC and AIC, as well as the addition of a new, higher crime rate group. The BIC for the 4-group model is -15625.58, and the AIC is -15583.64.

Table 19 presents the model fit diagnostics of the 4-group burglary crime rate trajectories. The model performs well at estimating the group assignment. The APP for each group is close to 1, the OCC is well above 5 for each group, and the estimated group probabilities match the proportion of the sample assigned to the group. The 95% confidence intervals for each group's estimated probabilities of membership are reasonably narrow.

Table 19. Burglary Crime Rate Trajectory Group Diagnostics of Assignment Accuracy

Group	$\hat{\pi}$	Ave. PP	OCC	P_j	95% C.I. for $\hat{\pi}$
Low Stable	0.39	0.99	154.85	0.39	0.35, 0.43
Mid-Low Decreasers	0.37	0.97	55.05	0.37	0.34, 0.41
Mid-High Decreasers	0.19	0.99	422.05	0.19	0.16, 0.22
High Decreasers	0.05	0.99	1881.00	0.05	0.04, 0.07

Figure 13 presents the 4-group crime rate trajectory.³¹ Recall that the average crime rate for the burglary data began around 1,800 burglaries per 100,000 and declined to 700 burglaries per 100,000. The first group is a low stable crime rate group, consisting of 39% of the sample. The crime rate begins at 1,000 burglaries per 100,000 population and declines slightly over time. Their crime rate is below the average. 37% of agencies belong to the mid-low decreasers. These agencies have a crime rate of 2,000 burglaries

³¹ The burglary crime rate results are presented here as the original 100,000 population calculation.

per 100,000 population and decline to around a rate of 1,000 burglaries. This group has a similar pattern to the average. The third group, the mid-high decrease (19%) begins at 2,500 burglaries and declines to around 2,000 burglaries per 100,000 population, showing a higher pattern of crimes than the average. Finally, the high decrease group consists of 5% of agencies. Their crime rate starts at 3,500 burglaries and drops to 2,500 burglaries per 100,000 population. The high decrease group is well above the average burglary crime rate.

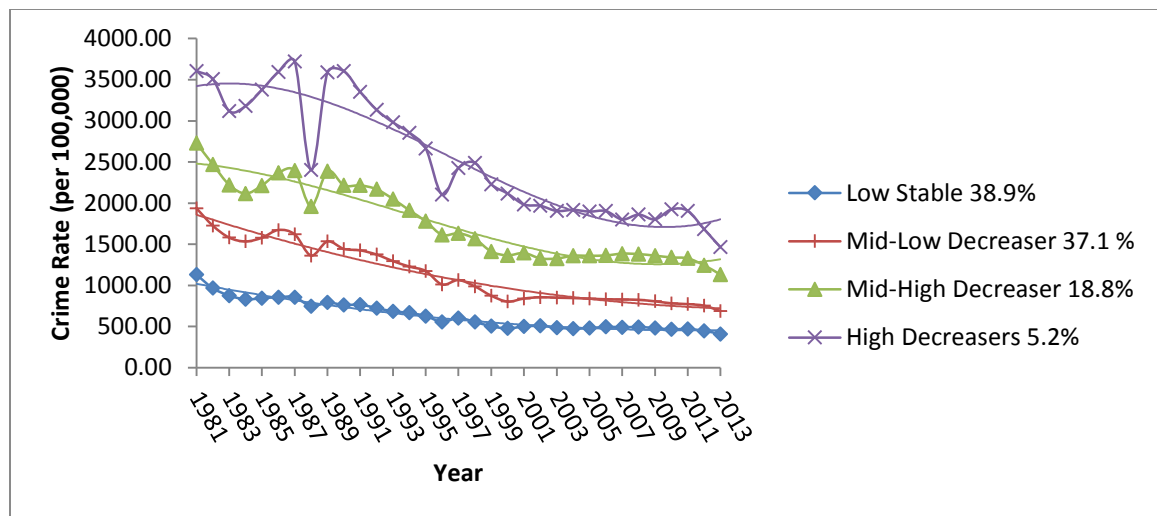


Figure 13. Burglary Crime Rate 4-Group Trajectory Solution (n=755)

Dual Trajectory of Burglary Crime Rates and Clearance Rates

The following three tables show the burglary dual trajectory results. Table 20 presents the probability of membership in a crime rate group given membership in a clearance rate group. Agencies with a high increasing then decreasing clearance trajectory are most likely to follow the low burglary rate group (75%). Having a low increasing or high decreasing clearance trajectory indicates greater probabilities of

membership in the low burglary rate group as well (51% and 46%). A low stable clearance rate indicates a higher probability of being in the middle-low (40%) crime rate groups. The results from this panel suggest that agencies with the three higher clearance rates are most likely to follow a low burglary rate membership. However, these clearance rates are both increasing and declining in performance over time.

Table 20. Burglary Probability of Crime Rate Group Conditional on Clearance Rate Group

Crime Rate Group	Clearance Rate Group			
	Low Stable	Low Increases	High Decreases	High Increases then Decreases
Low Stable	0.28	0.51	0.46	0.75
Mid-Low Decreases	0.40	0.37	0.35	0.16
Mid-High Decreases	0.25	0.10	0.16	0.03
High Decreases	0.07	0.02	0.03	0.06

Table 21 presents the probability of membership in a clearance rate trajectory given membership in a crime trajectory. Here, the highest probabilities are for membership in the low stable clearance rate group, regardless of crime rate group membership. The two highest burglary rate groups have the greatest likelihood of following the low stable clearance rate trajectory (75% probability for the high decreasing burglary rate, 74% for the mid-high decreasing burglary rate). The two lower burglary rate groups have a 59% (mid-low decreasing burglary rate) and 40% probability (low stable burglary rate) for following the low stable clearance group. The findings from this table suggest that the greatest probabilities for membership are in the low clearance trajectory, regardless of an agency's burglary rate.

Table 21. Burglary Probability of Clearance Rate Group Conditional on Crime Rate Group

Crime Rate Group	Clearance Rate group			
	Low Stable	Low Increases	High Decreases	High Increases then Decreases
Low Stable	0.40	0.34	0.16	0.09
Mid-Low Decreasers	0.59	0.26	0.13	0.02
Mid-High Decreasers	0.74	0.14	0.12	0.01
High Decreasers	0.75	0.10	0.09	0.05

Table 22 presents the joint probability of belonging to a crime rate and clearance rate group. Here, the highest probability is belonging to the low stable clearance rate group, despite the burglary rate group membership. For agencies in the low stable clearance group, there is a 16% probability of belonging to a low stable burglary rate trajectory, a 22% probability of being in the mid-low decreasing burglary rate, a 14% probability of belonging to the mid-high burglary rate group, and a 4% probability of belonging to a high decreasing burglary rate. There is also a 13% likelihood of belonging to the low stable burglary rate and the low increasing clearance trajectory. The overall results of the burglary dual trajectory analysis are not the same as the previous crimes. Here, it appears that the majority of agencies have a higher probability of belonging to the low stable or low increasing clearance trajectories, despite their burglary rate membership. Contrary to the other findings, those agencies with a low burglary rate do not perform better with their clearances; instead, they belong to one of the low clearance groups, although some do see an improvement over time if they fall into the low increasing clearance trajectory.

Table 22. Burglary Joint Probability in Clearance Rate Group and Crime Rate Group

Crime Rate Group	Clearance Rate Group			
	Low Stable	Low Increases	High Decreases	High Increases then Decreases
Low Stable	0.16	0.13	0.06	0.04
Mid-Low Decreases	0.22	0.10	0.05	0.01
Mid-High Decreases	0.14	0.03	0.02	0.00
High Decreases	0.04	0.01	0.01	0.00

Summary of Findings

The trajectory analysis of clearance rates demonstrates that there are variations in the average clearance rate, as found in the broader project.³² In every offense, there are increasing or decreasing clearance trajectories showing that agencies are improving or worsening their clearance performance. These trajectories deviate from the average clearance rate trend and offer a first step in developing hypotheses for understanding why agencies have different clearance patterns. The crime rate trajectories demonstrate that there are differences in crime from the average crime rate trend as well. Although all the crime rate trajectories follow a similar decreasing pattern over time (with a few stable trajectories), this visually depicts the different levels of crime rates among agencies.

The dual trajectory analysis revealed inconsistent relationships between crime rates and clearance rates among the offenses. For the conditional probability of how clearance rates follow crime rates, there was a trend that higher clearances tend to follow lower crime rates. However, the clearance trajectories were varied – while some

³² In the broader project, we conduct trajectory analysis for the sample used here, as well as a subsample of the largest 100 agencies.

clearances were improving, others were worsening over time. One finding that appears consistent among the four crimes, as demonstrated in the analysis in which the clearance rate is conditional on the crime rate, is that belonging to the highest crime rate trajectory has a greater probability of following a low decreasing or low stable clearance rate trajectory. Being cautious not to make causal assumptions, this negative relationship seems to suggest that agencies with high crime rates are less able to clear their crimes. This conclusion is more consistent and less variant than the finding that agencies with low stable crime rates also tended to belong to higher-performing clearance rate trajectories. The joint probabilities demonstrate variations among the offenses that I will discuss below.

A closer look at crime type indicates the variation in these results. The homicide crime rate conditional on the clearance rate demonstrated that agencies with a higher clearance rate (increasing and decreasing) had lower crime. The conditional probability of clearance rates conditional on crime rates showed higher crime was associated with lower clearances. For the homicide joint probability, a low stable homicide rate had a higher probability of belonging to a high increasing *and* high decreasing clearance rate. Although the clearance rates start high, some agencies perform better over time with low homicide rates, while other agencies get worse at clearing crime.

The robbery conditional probability of clearance rates on crime rates demonstrated a trend between low crime rates and clearance performance: as clearance rates declined, the chances of belonging to the low stable robbery rate also declined. The reverse conditional probability of crime rates on clearance rates demonstrated that high

robbery rates had a higher chance of belonging to a low clearance rate trajectory. The robbery joint probability showed the most consistent trend in the low stable crime rate. The low stable crime rate had a higher probability of belonging to several clearance trajectories: low increasing, middle decreasing, and middle increasing clearance rates. However, this finding indicates that some agencies are improving over time, but others are declining over time. No clear relationship emerges here, as variation exists in the clearance rate performance of the agencies.

Aggravated assault also has no clear relationships between the trajectories. The probability of membership in a crime rate group conditional on clearance rate group membership demonstrated those agencies with a high, but declining clearance rate had low assault rates. The low and middle increasing clearance rates were likely to follow the low and middle assault rate groups. For the probability of membership in a clearance rate group conditional on the crime rate, the high assault rate had a higher likelihood of following the lowest clearance trajectory. Additionally, the lowest assault rate group showed a higher probability of belonging to the two high decreasing clearance trajectories, as well as the middle increasing clearance trajectory, again demonstrating variation in clearance rate performance. The joint probability indicated lots of variation in placement among the trajectories. The probabilities were evenly spread out, indicating no relationship between clearance rates and crime rates.

The burglary results were somewhat different from the other findings. The probability of membership in a crime rate group conditional on the clearance rate demonstrated that higher clearances were likely to follow the low crime rates. However,

the probability of membership in a crime rate group conditional on the clearance rate results shows that regardless of the crime rate, agencies were more likely to follow the lowest clearance rate. The joint probability table produced similar results – agencies have a greater probability of belonging to the lowest clearance rate trajectory despite their burglary rate group. This finding seems to indicate that it does not matter how agencies perform in their clearance rate to belong to this low crime trajectory.

Once I conducted the initial dual trajectory analysis, I re-ran it for each offense by lagging the crime rate by one year. Therefore, I was examining whether the clearance rate from one year had an effect on the crime rate for the following year. The results were virtually the same for every offense. It may be because dual trajectory is not necessarily designed to examine the lagged relationship, or it may indicate that clearance rates do not affect crime rates. Since trajectory analysis is only exploratory, a different type of statistical analysis may be more optimal in trying to determine the causal relationship between crime rates and clearance rates.

Overall, the conditional probability findings indicate a negative correlation between high crime rates with low stable clearance rates. This implies that agencies that have the highest crime rates perform worse with their clearance. However, the remainder of the findings demonstrates no clear relationship. Although some of the low crime rates were associated with higher clearance rate trends, some of these clearance rates decline over time while others increased over time. No clear deterrent effect emerged from the trajectory findings.

CHAPTER FIVE: DISCUSSION AND CONCLUSION

The purpose of this study is to examine the relationship between crime rates and clearance rates using trajectory and dual trajectory analysis. The data utilized in this study includes the crimes of homicide, robbery, aggravated assault, and burglary for the years 1981-2013. Deterrence theory suggests that as clearance rates increase crime rates will decrease. Although some prior research has indicated a negative, deterrent relationship, other studies have found no connection between crime rates or clearance rates. Others have found a positive relationship, in which crime rates and clearance rates move in the same direction. Trajectory analysis is a new approach to examining this relationship, and it allows nuances to emerge from the national average crime and clearance rate trends by placing police agencies into trajectory groups based on their trends. Dual trajectory analysis determines whether there is a relationship between the crime rate trajectories and clearance rate trajectories of the agencies in the sample.

The trajectory analysis findings of the clearance rates did show variation in police agencies' clearance rates. Among all offenses, many clearance trajectories deviated from the average trend of the sample. The crime rate trajectories were all stable or declining but showed variation in the number of offenses among police agencies. The dual trajectory findings produced some interesting results. The conditional probability of clearance rates on crime rates indicated that higher clearance rates were associated with

lower crime rates. However, at closer examination, the clearance rate trajectories were much more varied. While some of these clearances were improving, others were worsening over time. No apparent deterrent effect emerged from the dual trajectory findings; instead, no clear relationship emerged. Another finding that appears consistent among the four crimes from the conditional probability of crime rates on clearance rates is that belonging to the highest crime rate trajectory indicates a greater probability of belonging to a low decreasing or low stable clearance rate trajectory. This is a negative relationship in the reverse – agencies with high crime rates are unable to clear their crimes effectively. Although the conditional probabilities do show some trends, the overall dual trajectory analysis showed no clear relationship between crime rates and clearance rates. However, the burglary results demonstrate that agencies are most likely to have a low clearance rate regardless of the crime rate.

The use of trajectory and dual trajectory analysis to examine the relationship between crime clearance and crime offers three important contributions. First, there is lots of variation found in clearance rates over time. National averages demonstrate the clearance rate has remained relatively stable over the last 35 years, with violent crimes having an average clearance of 46% while property crimes are cleared at a rate of 17% (Braga et al., 2011). The exception is homicide clearances, which have steadily decreased from 91% in 1965 to 64% in 2013 (Cronin et al., 2007). The average trends of the sample for this study also mirrored the national averages with robbery, aggravated assault, and burglary clearances remaining relatively stable. One interesting item to note is the homicide clearance average in my sample in this study is higher than averages in other

studies. This may be because other studies use weighted averages in which larger agencies are given more weight. My study includes smaller agencies, which may have fewer homicides and can clear homicides that do occur more efficiently. For example, the top 100 largest agency sample (used in the Arnold Foundation project) shows the homicides clearances are at a slightly lower level, but follow a similar pattern, beginning at 75% clearance and declining to 70% clearance, whereas my sample began at 82% and declined to 77%.

The clearance rate trajectory analyses for each offense demonstrate considerable variability in the clearance trends of police agencies. The solutions ranged from 3 distinct trajectories in homicide to 6 trajectories in aggravated assault. Although one clearance trajectory in each offense tends to follow the national average trend, the other trajectories show deviations from the trend. Certain agencies have improving clearances over time while others decline over time. Some of the agencies also start out much lower or higher than the average trend, and experience great changes in their clearance rate performance, but end up near the mean trend. These findings offer a starting point for developing hypotheses about why some agencies experience drastically different clearance rates.

Although not explored in this dissertation, there may be aspects of policing that create these variations across agencies' clearance rates. Scholars have examined certain characteristics of police agencies and how these may affect the agency's ability to clear crimes. Literature in this area demonstrates disagreement about certain findings. Some scholars find smaller or more rural communities are likely to have higher clearances (Cordner, 1989; Paré, Felson, & Ouimet, 2007), although Chaiken and colleagues (1976)

find that larger police departments have higher clearance rates. Larger police departments are likely to be in cities and more populated areas. Researchers have also found that agencies with a greater number of reported crimes have lower clearances (Chaiken et al., 1976; Tilley et al., 2007). This is also indicative of larger agencies in higher-populated areas.

Other researchers examine agency factors in training and work. Agencies with a heavier workload had lower clearance rates (Cordner, 1989). An increase in police expenditures, officers, or training did not seem to improve or have any impact on clearance rates (Chaiken, 1975; Davies, 2007), although a survey of police agencies conducted by Horvath, Meesig, and Lee (2001) find police believe increases in personnel, technology, and training were needed to help increase clearance rates. Another study examines centralizing detective units and finds that the centralization of a robbery unit was associated with increases in cases cleared, allowing for better communication among detectives (McCluskey, Cancino, Tillyer, & Tillyer, 2014).

Additionally, clearance rates may vary by department based on the department's classification, and administrative practices may change within the department (Chaiken, 1975; Chaiken et al., 1976). One police department may classify crimes differently than another, or departments may change classifications to achieve certain crime reduction goals within the department. These classifications may affect the crime rate/clearance rate relationship. The literature examining the relationship between agency characteristics and clearance rates is inconclusive, as there is some disagreement between findings. There appears to be any number of organizational factors that may affect an agency's ability to

clear crime. The present study provides a starting point for identifying different clearance trajectories into which an agency may fall. The Arnold Foundation project, of which this dissertation is a part, will further examine the relationship between agency factors and clearance rates, using trajectories of clearance rates to study how agency characteristics may differ across various clearance trajectories. This project will allow for further development of hypotheses based on clearance trajectories and agency organizational characteristics.

In addition to organizational aspects of police agencies, police investigations may also play a role in an agency's clearance rate. The RAND study on investigators in the 1970s was the first extensive examination of the role and effectiveness of investigators (Chaiken, 1975; Greenwood & Petersilia, 1975; Chaiken et al., 1976). The main findings of these series of studies indicate the most important factor in solving a case is from information from the victim given to the responding patrol officer. They estimate that about 30% of crimes are cleared at the scene by the responding patrol officers, 50% are cleared because the offender is known when police take the first report, and about 2.7% of clearances are attributed to special techniques investigators use (Chaiken et al., 1976). Other research also finds that most crimes are solved at the scene through actions of the patrol officers or identifying suspects on the scene (Willman & Snortum, 1984; Wellford et al., 1999; Horvath et al., 2001). Although a majority of the literature seems to indicate that patrol officers make at least half of the arrests, investigators are still producing arrests and their effectiveness is measured by their arrests.

While there is some literature examining the effectiveness of investigators in deterring crime, more research is needed on the investigator role and the process of investigations and how this may affect clearance rates. For example, a centralized detective unit may belong to a high-performing clearance trajectory because it is easier to communicate and coordinate than a decentralized unit (McCluskey et al., 2014). Other research looks at the amount of time spent at the scene of the crime, the number of investigators assigned to the case, whether investigators interview witnesses and collect evidence, and if detectives have the proper equipment to perform investigations (see Brandl & Frank, 1994; Carter & Carter, 2015; Coupe, 2014; Coupe & Griffiths, 1996; Cronin et al., 2007; Eck, 1983; Wellford & Cronin, 1999). In the broader project of which this study is a part, we will explore these questions through a deep case study of agency investigative units and case files.

The second contribution of this analysis is that it continues to build evidence that there seems to be no clear relationship between crime rates and clearance rates, which is seen when examining specific types of crimes. There appear to be trends in which higher clearance rates are associated with low crime rates. However, a closer look at the results demonstrates much more variation among these trajectories. The clearance rate trajectories associated with the low crime rates perform differently over time, with both increasing and decreasing clearance trajectories associated with low crime rates. Therefore, these results indicate that no clear relationship exists between clearance rates and crime rates with one exception. There is a negative correlation, although not in the form of a deterrent effect, with high crime rates associated with low clearance rates found

in all crimes. This negative correlation may suggest a system overload – when crime rates are high, police are overloaded and unable to effectively clear crime (Logan, 1975; Geerken & Gove, 1977).

One interesting pattern found in the dual trajectory analysis is that while there was no clear relationship in homicide, robbery, or assault, there appears to be a pattern in the burglary findings, in which agencies are likely to be within the low clearance rate trajectory regardless of the crime rate trajectory. In other words, no matter an agency's level of offenses, an agency has a greater probability of belonging to the lowest performing clearance trajectory. Nearly 55% of the agencies belonged to the low stable clearance rate group, indicating less variation in the burglary clearance rate as compared to the other offenses. This may be because of the nature of burglary itself – it is a property crime that has the lowest clearance rate among the other offenses and is harder for police to clear. There appears to be more variation among the dual trajectory findings and the clearance rates themselves for the violent offenses as compared to the property crime of burglary. It seems that approximately the same rate of burglaries are solved, despite the level of crime. Perhaps certain factors are more likely to affect violent crimes, which influence the variations found in those findings.

The predominant theory outlining the relationship between crime rates and clearance rates is deterrence theory, which states that as clearance rates increase, the crime rates decrease. If police are effective or become more efficient over time in their ability to solve and clear crimes, this may act as a deterrent to potential offenders and prevent future crimes from occurring, thereby reducing the crime rate. Many studies have

found evidence of a deterrent effect (Brown, 1978; Chamlin, 1991; D'Alessio & Stolzenberg, 1998; Geerken & Gove, 1977; Tittle & Rowe, 1974; Wellford, 1974). However, in the present study, there is too much variation in the relationship between crime rates and clearance rates to draw a conclusion about the deterrent effect of case clearances on crime rates. The crime rate trajectories in this study are either stable or decreasing over time, except the highest crime rate trajectory in the homicide and assault models, which first increased, but ended up decreasing over time. All crime trajectories trend in a stable or declining pattern. Based on deterrence theory, because crime is declining, the clearance rate should be increasing. However, the clearance trajectories in all crime types are varied. There are likely other reasons why the crime rate is declining, such as a natural decrease. However, the fluctuations in clearance rates indicate there is much unanswered about how police conduct arrests and investigations. There is no clear association between a declining crime rate trajectory and clearance performance due to the significant fluctuation of the clearance rates.

A closer examination by offense of the increasing clearance trajectories does not support a deterrent relationship. According to deterrence theory, an increasing clearance rate should be linked to a decreasing crime rate. The increasing homicide clearance trajectory was associated with a low and stable crime rate trajectory; however, the high decreasing homicide clearance trajectory had a higher probability of being associated with the low stable crime rate than the high increasing clearance trajectory. The two increasing robbery clearance trajectories are associated with a stable crime trajectory, showing no deterrent relationship. The two increasing assault clearance trajectories are

associated with the two lowest and stable assault crime trajectories. The one increasing burglary clearance trajectory is related to the low stable and low decreasing crime rate trajectories, but again, all clearance trajectories were associated with the lowest two burglary crime rate trajectories, not indicating evidence of a deterrent effect.

Additionally, the increasing clearance trajectories are fewer than the decreasing clearance trajectories in each crime type. In homicide, only one of the three clearance trajectories is increasing. There are two increasing clearance trajectories in both robbery (out of five total) and assault (out of six total clearance trajectories). Burglary only contains one increasing clearance trajectory out of four. Only the robbery low increasing clearance trajectory contained a majority of agencies (nearly 36%) within each offense. This suggests that the magnitude of rising clearance rates is not as great when compared to the decline in clearances. Because the levels of increasing clearance rates are not as high, it is not enough to impact crime rates, which contribute to the finding of no relationship between crime rates and clearance rates.

In summary, the increasing clearance trajectories are most related to stable crime rate trajectories, indicating no changes in the crime rate due to the clearance rate. Evidence of a deterrent relationship found by previous researchers showing a tipping effect (Brown, 1978; Chamlin, 1991; Tittle & Rowe, 1974), or based on the “rationality” of offense type where rational crimes are more likely to indicate a deterrent effect (Geerken & Gove, 1977) is not found in the present study, although this study is not the best test of the tipping effect. Additionally, the magnitude of increasing clearance rates in

this study is not as strong as the declining clearance trajectories, suggesting that the level of increasing clearances is not enough to impact crime.

Perhaps the relationship between crime rates and clearance rates at the macro-level is not evident enough to create a deterrent effect. It may be that the measure of deterrence may be more easily captured at the individual level, in which specific activities are measured instead. For example, Nagin (2013) describes studies that examine the effect of police numbers on the crime rate has shown some evidence of a deterrent effect in the increase in the amount of police (see Di Tella & Schargrodsky, 2004; Evans & Owens, 2007; Klick & Tabarrok, 2005; Levitt, 1997; Marvell & Moody, 1996). Nagin (2013) also describes how changes in police activity, such as hot spots or problem-oriented policing also decrease the crime rate (see Braga, Papachristos, & Hureau, 2012; Sherman & Weisburd, 1995 for hot spots policing studies; also see Kennedy et al., 2001; Braga & Weisburd, 2012 for problem-oriented policing on the pulling levers strategy). Therefore, how police levels or police activities affect crime rates may create a more noticeable deterrent effect. The perceptual deterrence literature, as summarized by Nagin (1998, 2013) indicates that scenario-based studies which examine the situational effect of the risk show that if people believe the sanction is certain, such as police presence and apprehension by the police, they are less likely to engage in crime in that situation. Therefore, shifting from a general level of focus on the relationship between crime rates and clearance rates to a more individual level of certainty of apprehension may show more evidence of deterrence.

However, this shift in focus leads to the question of whether clearance rates are an appropriate measure of the deterrent effect created. As Nagin (2013) and Nagin and colleagues (2015) describe, police in their role as apprehension agents indicate that when police make an arrest for a crime committed, the police have failed at preventing that crime from occurring in the first place, although the police have succeeded in their apprehension role. So while clearance rates or arrests rates may be a measure for the police in the apprehension role, a different measure is required of police in their sentinel role, in which police prevent from occurring in the first place (Nagin, 2013; Nagin et al., 2015). In the sentinel role, the police are reducing the probability that a criminal opportunity can be completed. Therefore, policing methods such as hot spots policing are a better measure of deterrence at preventing crime for occurring in the first place. However, shifting policing from the apprehension role to the sentinel role is challenging as noted in the two Nagin articles, as police performance is often measured based on their ability to make arrest in the apprehension agent role.

Another type of relationship that may occur is a positive correlation. As crime rates increase, clearance rates increase as well. The reverse is also true - crime rates decrease, and clearance rates decline, too. Decker and Kohfeld (1985) find a positive relationship with homicide, robbery, and burglary, in which the crime and clearance rate both increase. Here, I found one stable robbery crime trajectory associated with a stable clearance trajectory, and an associated stable crime and clearance burglary trajectory as well as a linked declining crime and clearance burglary trajectory. These results of the stable trajectories seem to indicate that police activity has not changed, and has not

affected the crime rate in any way. The declining burglary crime and clearance trajectories may suggest that as crime declines, so do the number of police (Tittle & Rowe, 1974). Since the crime rate is already decreasing, the number of police declines, or perhaps police do not expend as much energy on clearing the actual crime, leaving the clearance rate to decline as well. Alternatively, as the number of crime and solvable cases decreases, the easier solved cases decrease as well, leaving only more challenging cases left and a declining clearance rate (Cook, 1979). Overall, there is no strong indication of a positive relationship between crime rates and clearance rates from the dual trajectory results.

The third type of relationship often found when examining the relationship between crime rates and clearance rates is no clear relationship between the two variables (Chamlin, 1988; Chamlin & Myer, 2009; Greenberg & Kessler, 1982). This is the main finding of this study. This finding may indicate that clearance rates and crime rates are simply not related. Changes in the clearance rate may not be noticeable enough to potential offenders to create a deterrent effect of lower crime rates (Greenberg & Kessler, 1982). Other factors may be impacting this relationship, such as certain agency organizational characteristics as discussed above. Agency size (Chaiken et al., 1976; Cordner, 1989; Paré et al., 2007; Tilley et al., 2007), agency workload (Cordner, 1989), police expenditures and training (Chaiken, 1975; Davies, 2007), the centralization or decentralization of detectives units (McCluskey et al., 2014), or even how departments classify their crimes and clearances (Chaiken et al., 1976) may impact how agencies clear crime; which may impact the crime rate and clearance rate relationship. Community

factors may also influence clearance rates. For example, Roberts (2008) finds robbery and assault clearances are lower in areas with higher unemployment and racial segregation. However, Paré et al., (2007) find that crime clearance is greater in poorer communities. The mixed findings may point to some of these contextual factors that vary from place to place. Given the different trends found between the violent crimes and property crimes here, violent crimes may be more influenced by some of these factors, whereas burglary seems to be harder to clear. These factors cannot be solved in the present study, but are important to consider when thinking about future research on the relationship between crime rates and clearance rates.

One issue that this study cannot solve is the causality of the relationship between crime rates and clearance rates. Although I performed a lagged analysis in the present study, the results were virtually the same as the contemporaneous analysis. As trajectory and dual trajectory analysis are exploratory in nature, this method is not the most suitable for determining the directional causality of this relationship. The dual trajectory analysis provides a probability of association – that is, one clearance trajectory is associated with a certain crime trajectory. Therefore, it appears that crime rates and clearance rates are not related to each other based on the findings of this study.

The third contribution of this study is methodological, using dual trajectory analysis to help shed more light on the relationship between crime rates and clearance rates. This method offers an improvement over cross-sectional studies and shorter longitudinal studies, as the present study uses over 30 years of data to provide a better picture of the trends of clearance rates and crime rates over time. Although trajectory

analysis is exploratory, it can be useful in developing hypotheses because it categorizes the sample based on similar trends (Nagin, 2005). Additionally, trajectory analysis provides a visual representation of the trajectories that helps to demonstrate the differences in the trajectories. This visual representation is an improvement over other methodologies because it can depict the variations in the levels and groupings of the trends. Indeed, the trajectory analysis demonstrates considerable variation in the clearance rate trends over time. The placement of police agencies into trajectories based on their clearance rate is a starting point for identifying different patterns of clearance, and what may affect a police agency's ability to clear crime. Many hypotheses can be developed from these trajectories.

Overall, the dual trajectory analysis did not solve the question of whether crime rates and clearance rates are related. There are not many increasing clearance trajectories in any of the offenses, and the findings do not indicate these agencies had anything to do with decreasing crime trends. There is still the question of whether increasing clearances may reduce crime, but this study may not necessarily be the best test of this because there were so few increasing clearance trajectories. The dual trajectory analysis also offers a new way to examine this relationship, which is still not clearly resolved by prior research. Although no clear conclusion can be reached about the relationship between crime rates and clearance rates, it is still a useful endeavor, because it demonstrates the complexity with which these trends unfold over time.

Limitations

There are several limitations to this study. The first limitation is the UCR data itself. The issue of missing data and reporting issues to the UCR program is problematic. Agencies do not consistently report from year to year. Sometimes, only crime counts are reported and not clearance counts. Smaller agencies and certain state agency reporting programs have large amounts of missing data across much of the time span. Additionally, the UCR does not differentiate between missing data and a true zero for the number of crime offenses and clearances. It is not possible to determine whether an agency did not report their numbers to the UCR, or whether the agency reported zero occurrences of crime or clearance for that particular entry.

I attempted to deal with this limitation by limiting as much missing data as possible while retaining a large sample size. Using agencies with 100 or more authorized sworn officers as defined by LEMAS reduced a significant number of missing data. I attempted to deal with the missing data problem by applying rules to delete agencies with some degree of missing data to minimize this issue. Despite these limitations with the UCR data, it is still the best data to use for this study. The UCR program has consistently collected crime data from police agencies since the 1930s, and collects from a large number of agencies in the U.S. Even with the missing data problem, there are a large number of agencies that consistently report their crime data every year, allowing for a large sample size and longitudinal analysis of these agencies. Additionally, the data is reported by the police agencies themselves, and the unit of analysis of this study is police agencies. This data allows for a longitudinal examination of the relationship between crime rates and clearance rates of police agencies.

The second limitation is the calculation of the clearance rates. There has been debate about whether clearance rates are an effective measure of police performance in clearing crime, as well as criticism about the calculation itself. The UCR does not distinguish between crimes cleared by arrest and crimes cleared by exceptional means; therefore, this may inflate the agencies' clearance numbers and not truly reflect the actual performance (Jarvis & Regoeczi, 2009). Additionally, the clearance rate may include crime as cleared that occurred in a different year. It is possible to have a clearance rate over 100% if cleared crimes from previous years are counted for that year. Cook (1979) argues that the clearance rate does not accurately assess the deterrent effect of the risk posed from apprehension of police; therefore, it is a faulty measure of police performance on crime (see also Nagin, Solow, & Lum, 2015). Gibbs and Firebaugh (1990) demonstrate how the clearance rate calculation may contain measurement error, which may underrepresent the number of reported crimes but overestimate the number of clearances, resulting in a negative relationship. Other studies in deterrence literature use the number of arrests, or the arrest rate, which may have provided different results. Arrest rates may increase (or decrease) but the clearance rate may remain stable if the increase (or decrease) in arrests and crime is proportional. Arrests or arrest rates may be a more effective measure of police performance over clearance rates. Arrests may be a better association of offenders' perception of risk and therefore may be a better measure to assess deterrence.

Despite these criticisms about the calculation of clearance rates themselves, and its use as a measure of police performance, it is still widely used in deterrence research. It

is also one of the few indicators available to examine police performance and investigator effectiveness. The widespread reporting of crime clearance to the UCR data provides easy access to these numbers, whereas obtaining other measures of police investigative performance from hundreds of police agencies would be a time-consuming challenge. The use of the number of arrests or arrest rates in this study would have required a separate type of data from the UCR data I used here. There would likely have been a discrepancy in the amount of data I would have been able to collect, resulting in a lower sample size.

A third limitation is the exploratory nature of trajectory analysis. As Nagin (2005) discusses in his book, groups are an approximation, and individual agencies may not directly follow the trend of their trajectory group placement over time. Additionally, model selections can change with the addition or subtraction of cases. Selection of a final model is not definitive, as the BIC and AIC are only used as a guide, and one of the factors to look at when selecting a final model. However, trajectory analysis allows for a visual representation of how different groups behave over time, rather than just the average performance of all samples in the analysis. Further, the use of dual trajectory analysis provides probabilities of the linkages of two behaviors over time, and how these trends occur or differ together.

The final limitation of this study is that trajectory analysis does not solve the simultaneity issue regarding the relationship between crime rates and clearance rates. Prior deterrence research using cross-sectional studies has unsuccessfully been able to untangle the causality in the relationship between crime rates and clearance rates.

Longitudinal studies have produced inconsistent results and tend to focus on one or a few locations, which is not generalizable to other areas. Although I lagged the results for dual trajectory analysis, the results were virtually the same as the contemporaneous results. Dual trajectory analysis may not be the most useful method to determine the causal relationship between crime rates and clearance rates. However, the dual trajectory method is useful as a starting point to see how the trends of crime rates and clearance rates unfold together over time by linking these trends together. This study cannot resolve the causality issue.

Suggestions for Future Research

Trajectory analysis places agencies into trajectories based on their crime rates and clearance rates, and dual trajectory determines how the two trends link over time. Dual trajectory provides a starting point for identifying how agencies deviate from average trends and placing them into trajectory groups based on their crime and clearances. The results of this study provide several implications for future research. The findings show no clear relationship between crime rate and clearance rate trends, except linking high crime rates and low clearance rates. Therefore, the next steps for future research would be to look more closely at why agencies fall into particular clearance trends.

As already mentioned, this study is part of a larger project that intends to examine clearance rate trajectories and investigative effectiveness. Currently, the project has reviewed the clearance rate trajectories of two samples – my sample used here and the top 100 largest police agencies in the U.S. Dual trajectory analysis has also been conducted on the top 100 sample, with similar findings to this analysis. Moving forward,

the remainder of the project will select agencies to examine within high performing and low performing clearance rate groups, to better understand their policies, practices, and investigative case processing. The goal of the project is to understand better how agency investigative practices may impact their clearance rate.

However, the project is only examining the top 100-agency sample for the remainder of the project steps. It may be interesting for future research to follow the LEMAS analysis and more closely explore the case clearances in smaller agencies. Prior research has found that smaller agencies are more efficient at clearing crime than larger agencies (Cordner, 1989; Paré, Felson, & Ouimet, 2007). My sample here provides agencies with at least 100 police officers. It may be interesting to explore these agencies similarly as will be done in the project to determine whether there are investigative differences between the sizes of agencies. An interesting examination may also compare agency size and population in the highest clearance trajectories to the lowest clearance trajectories across all offenses.

An additional possibility for future research is to try to find some way to conceptualize better police investigative efforts at clearing crime other than the clearance rate. Based on criticisms previously mentioned with the measure of the clearance rate, and the findings of this study indicating no relationship between crime rates and clearance rates, some other measure may be better at determining police effectiveness in investigations. The number of arrests or the arrest rate may be a better measure. The Arnold Foundation project may provide a starting point by going into a small sample of police agencies to take a closer look at their investigative methods. Criminology literature

needs more research on police investigations, which may help with the conceptualization of measures other than the clearance rate for investigative performance. Additionally, shifting away from the apprehension role of the police to the sentinel role of police may offer a better study on the deterrent ability of police on crime. However, this will require changing the focus from arrests and clearance rates to measures that capture the ability of police to be a guardian who prevents the criminal act from occurring in the first place.

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