The Spatial Effect of AB 109 (Public Safety Realignment) on Crime Rates in San
Diego County

By

Charles Dixon Jones

A Thesis Presented to the
Faculty of the USC Graduate School
University of Southern California
In Partial Fulfillment of the
Requirements for the Degree
Master of Science
(Geographic Information Science and Technology)

May 2016

To my beautiful, wonderful, amazing wife Darci, and Mother and Father without whose support this project would not have been possible.

Table of Contents

List of Figures

List of Tables

Acknowledgements

List of Abbreviations

GIS   Geographic information system

GISci   Geographic information science

SSI   Spatial Sciences Institute

USC   University of Southern California

CDCR   California Department of Corrections and Rehabilitation

MAUP   Modifiable Areal Unit Problem

NIBRS   National Incident Based Reporting System

OLS   Ordinary Least Squares

FBI   Federal Bureau of Investigation

CSV   Comma Separated Value

MS   Mandatory Supervision

PCRS   Post Release Community Supervision\

SANDAG   San Diego Association of Governments

Abstract

AB 109 (Public Safety Realignment) widely changed the way criminal offenders are processed in California, starting 1 October 2011. It is widely purported that AB 109 is affecting crime rates in the State of California. This paper studies the spatial effects of AB 109 on crime rates in San Diego County. Studies have shown Criminal Offenders will likely commit offenses near their place of residence. Recidivism is a complex and serious problem in California, the United States and the World. Regression and hot spot analysis as well as traditional statistics methods were used to analyze crime rates, or crime events per 1000 persons at the census tract level. Five categories of crime were studied: AB 109 categorized offenses or offenses falling under the AB 109 statute, Non AB 109 offenses, Crimes Against Persons, Crimes Against Property and Crimes Against Society. Analyses indicated that crime rates for most categories studied decreased. Property crime rates exhibited a median increase of 0.7 events per 1000 persons at the census tract level. Spatial OLS analysis indicated a correlation between residence locations of AB 109 offenders and a hot spot of property crime rate increase however the model was misspecified. Other category hot spots exhibited no correlation with AB 109 offenders. Variance of the crimes against persons hot spot was explained by different variables. Some other combination of complex variables not listed or tested as part of this study is responsible for the variance of the hot spots of other categories. The implementation of AB 109 appears to have been successful in that offenders are being diverted to County facilities and reducing the State prison populations and is associated with several categories of crime rate decrease in San Diego County. However property crime has exhibited a statistically significant increase in crime rates across San Diego County coinciding with AB 109. However no significant correlation was found between populations of AB 109 offenders and crime rate increase of any categories.

Chapter 1 Introduction

1.1 Background

A constitutional guarantee of the United States is to protect the "Life, Liberty and Property" of

its citizenry (Heyman, 1991, pp.512). As a primary function of this guarantee, it can be inferred

that it is the government's duty to make every effort to prevent crime and apprehend criminals.

At the center of this assumption is the new California law, "AB 109" or "Public Safety

Realignment." As a result of the excessive overcrowding of California's State Prisons, and a

Supreme Court order to reduce the number of inmates housed in the State Prison system, the

"Public Safety Realignment Act" was passed in 2011 in an effort to mitigate the overcrowding of

California's State Prisons (Couzens, 2013 pp.217; Weisberg and Quan, 2014).

This new law represents a "significant change" in the way convicted offenders are

sentenced. Specifically "non-serious, nonviolent or non-sex" offenders will now serve time in

"county jail" or receive a "sentence" of "probation" as a replacement for the "State" correctional

facility "sentence" they would have received before the new law (Californians for Safety and

Justice, 2013). Additionally, "AB 109," represents a change in the way offenders will serve time

while remanded and a change in post remand correctional supervision. Previously, offenders of

the AB 109 type offenses would typically serve time in a State correctional facility and would be

supervised by the State Parole board post release. Under AB 109, offenders will now serve their

sentence in county jail, serve probation only with no remand, or have their sentence split

between county jail and county probation with no post remand supervision (Couzens, 2013 pp.

218).

AB 109 was signed into law in April of 2011 and took effect in October 2011; Its primary

purpose was to decrease the number of inmates remanded to the State prisons from 150,000 to

110, 000 and continue this trend (Californians for Safety and Justice, 2013). As a consequence, the obligation to supervise those convicted of "non-serious, nonviolent or non-sex felony offenses" was shifted from the State of California to the Counties of California (Californians for Safety and Justice, 2013). Current offenders serving a sentence in state prison are not released early as a result of this legislation, however all future convictions will be punished in this manner (Californians for Safety and Justice, 2013). As a result of this shift in sentencing and supervision, it is vital to understand the relationships between the new law, offenders, and crime rates.

This work attempts to study the relationship, if any, between offenders sentenced under the AB 109 provision and crime rates. The methods used to evaluate and identify this and other relationships is described further in Chapter 3.

1.2 History of the CDCR

The History of the CDCR or the California Department of Corrections and Rehabilitation is fascinating, and as this work attempts to study the effect of a law designed to affect the prison population, it is important to understand the history of the CDCR. California is known as the Golden State, and if gold was measured in terms of population, it seems to live up to its name. During the 2010 Census, California's total population was recorded as 37,253,956; up 10% from 33,871,648 in 2000. (U.S. Census Bureau, 2015; U.S. Census Bureau, 2002).

With any growth in population it should be expected that the rate of persons incarcerated would grow at the same rate. In California, this was the case for many years, however toward the end of the 20th century the numbers or persons imprisoned and ratio of persons per total population grew sharply (Zimring and Hawkins, 1994). Zimring and Hawkins note that the numbers of persons imprisoned grew at a stable ratio from 1950 to 1970 however in the "1980s"

the number of persons imprisoned increased from "24,569" to "97,309" by 1990, an increase of 296% (Zimring and Hawkins, 1994 pp. 84).

Before the population explosion, the State prison system had sites focused on offender rehabilitation. At one site, "Chino," there was a different philosophy, vocational training and education for inmates, however, at one point the vocational training disappeared (Wilkinson, 2005 pp. 10). After the disappearance of certain rehabilitation programs, the prisons appear to have continued to deteriorate to the point that the Supreme Court determined the "health care" provided by the CDCR was in violation of the Constitution due to extreme poor quality (Californians for Safety and Justice, 2013).

As a result of the poor "health care," a "2009 a three judge… order" mandated reduction of "prison population" (Weisberg and Quan, 2014 pp. 7). The "U.S. Supreme Court" upheld the decision and found "prison overcrowding to be 'the primary cause of the state's unconstitutional failure to provide adequate medical and mental health care to California prisoners" (Weisberg and Quan, 2014 pp. 15).

1.3 Justification

Many people and organizations are striving to understand the effects of AB 109 and its relationship to crime rates. Many authors and organizations have researched this issue and concluded that crime rates have risen since the implementation of AB 109 (Beard et al, 2013; Lofstrom and Raphael, 2013,). A Public Policy Institute report authored by Magnus Lofstrom and Steven Raphael indicates "violent" and "property crime [rates]" are "up" in California (Lofstrom and Raphael, 2013, pp 2). The report contends the "increase in violent crime" seems to be a societal inclination toward increased "violent crime" exhibited in "other states," however the report also found "robust evidence that realignment is related to increased property crime"

(Lofstrom and Raphael, 2013, pp 2). Additionally a report published by the CDCR indicates the probability of "offenders released… during the first year" of AB 109 to be detained for a "felony" was higher "post-realignment" and "offenders" were detained for a "serious or violent" crime at a higher rate than pre- AB 109 (Beard et al, 2013 pp i-ii).

The studied effects of AB 109 are not all negative. The CDCR report mentioned above, published in December 2013, indicates "that there [was] very little difference between the one-year arrest and conviction rates of offenders released pre- and post-Realignment" (Beard et al, 2013 pp i).

Due to the nature of AB 109 unintended consequences of the statute have presented themselves. Due to the shifting of responsibility for offenders, subject to the AB 109 provision, from the state to the counties, it has been found that county incarceration facilities are reaching capacity due to the increase in inmates and as a result, more counties are reporting the early release of inmates (Beard et al, 2013; Lofstrom and Raphael, 2013). According to the *Californians for Safety and Justice* website that outlines the changes that have taken place under AB 109, no inmates have been released from "State Prison" before their sentence was completed because of AB 109, and AB 109 has not changed "sentence lengths" as prescribed in the "penal code" (Californians for Safety and Justice, 2013). As AB 109 was not intended to release inmates from prison early, and was designed to abide by the existing prescribed sentences by law; if an offender who would have been serving their sentence in the State Prison previously, and would now serve their sentence in a county facility, being potentially released early, would certainly represent an unintended consequence of the law.

The unintended consequence of early release of inmates together with the uncertain nature of crime trends in California related to the implementation of AB 109 are the prime

motivations for this study. As new laws are passed and implemented, an understanding of the effects and consequences of laws are necessary to move forward as an educated and informed society.

1.4 Research Questions and Objectives

This study analyzes crime rates, comparing two main temporal periods, to determine the effect of a new law on society. To conduct this analysis, four research questions were asked:

1) What is the trend in reported crime rates in San Diego County before and after the implementation of AB 109? And what is the spatial distribution of reported crimes?

2) Which types of crime are increasing?

3) Are populations of offenders sentenced under the AB 109 provision correlated with crime rate increase?

4) Are other factors or variables responsible for crime rate increase?

Three research objectives were identified to help answer these questions. First: Determine the median crime rate change and statistical significance for crime categories. Second: Determine correlation between hot spot of crime rate increase for each crime category studied and populations of AB 109 offenders. Third and finally: Determine the correlation between hot spot of crime rate increase for each crime category studied and other explanatory variables.

The methods and data behind each of the aforementioned objectives are explained in greater detail in Chapter 3 Methods and Data.

1.5 San Diego County

San Diego County is home to 3,095,313 persons or 8.3% of the total population of California, as counted in the 2010 Census, and was chosen as the region for this study.

San Diego has a very mild climate with low variability in weather and temperature (Cities of the United States, 2006). Sandi Cain, of the San Diego Business Journal noted "San Diego County is a microcosm of the entire state, embracing coastal resorts and plains, foothills, mountains and desert. Its rejuvenated downtown has a mix of commerce, residents and visitors that makes it a vibrant community" (Cain, 2005). As the physical geography of San Diego provides wide variability and the population provides a large sample size of the population of the
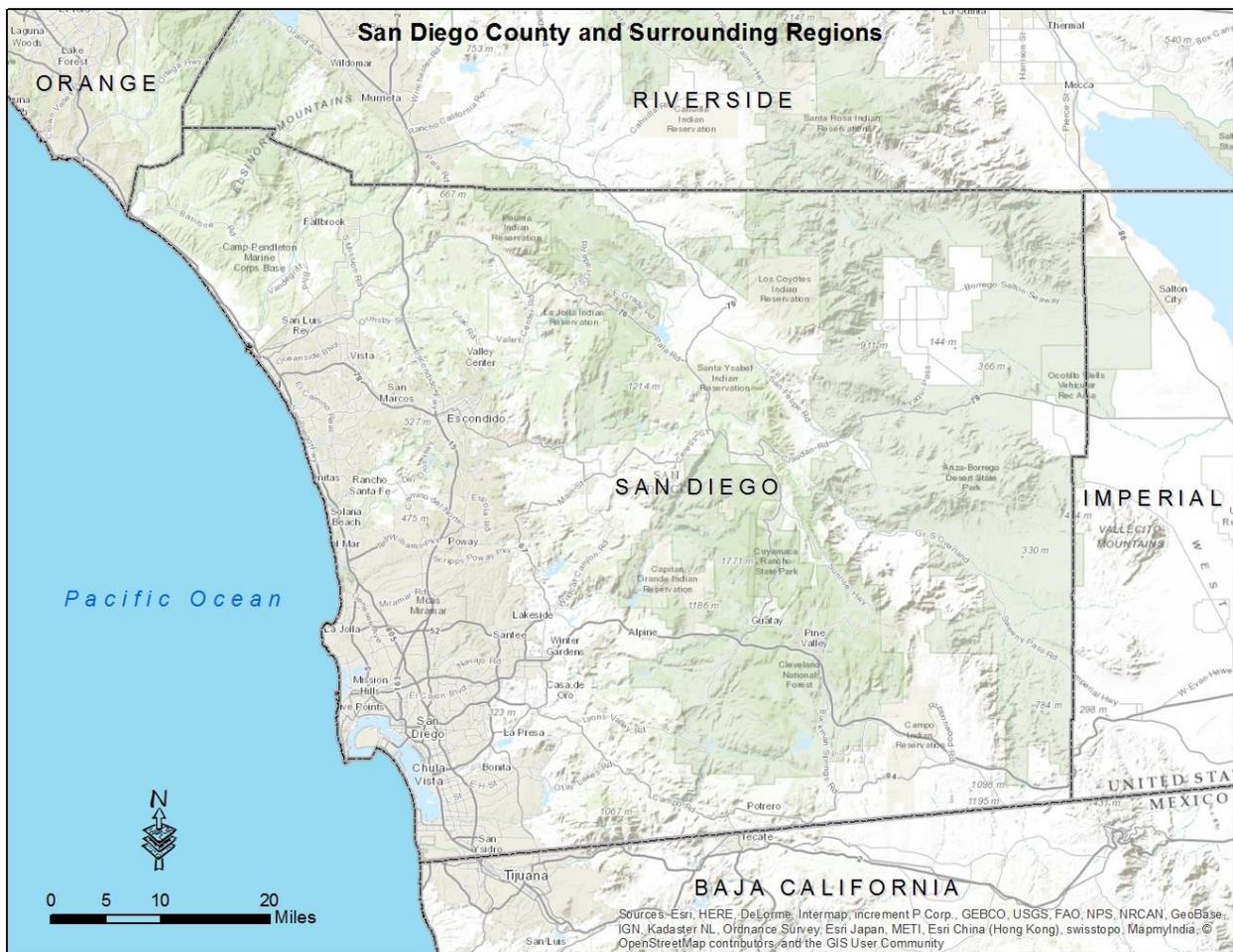
Figure 1: San Diego County and Surrounding Regions

state, the region was selected for this study. The San Diego County Region is displayed in Figure 1.

Because San Diego County is home to a large population and contains a wide variation in physical geography, the population of the County is widely dispersed. Figure 2 was generated by creating random points using data from Census Tract polygons thereby estimating the actual distribution of population in the County and creating a nice kernel density display of the population density of the County.
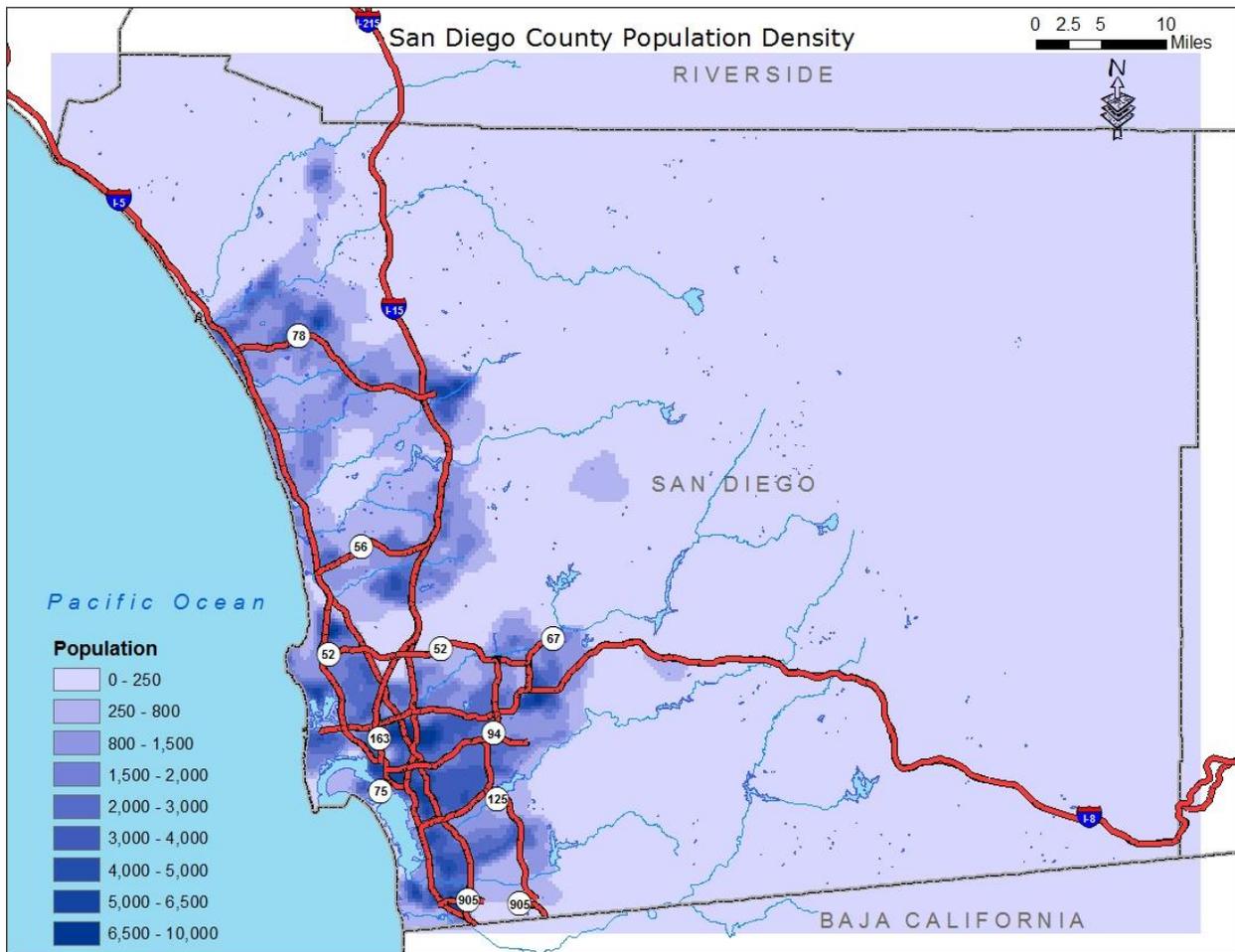
Figure 2: San Diego County Population Density

1.6 Thesis Organization

The organization of this paper is as follows: the paper begins with a review of relevant crime and offender literature that lays the foundation for the research contained in the document.

Following the literature review, Chapter 3 contains a section detailing the methods and data used in the study. This section describes how multiple sources were used to obtain crime and offender data, as well as a detailed explanation of the data processing methods, such as how zonal statistics and geocoding were performed. The methods and data section also contains a brief section detailing the geographic study area of San Diego County.

Chapter 4 of this work contains a detailed explanation of the analysis results. An inferential statistical and spatial statistical analysis were performed on the Crime Data for San Diego County. The results of the analysis, including an ordinary least squares (OLS) and spatial regression analysis of the relationship between offender residence locations and crime rate increase hot spots, are explored in this section.

The final chapter, Discussion and Conclusion, explores the results of the study in depth and provides a sources of error discussion as well as future work recommendations.

Chapter 2 Literature Review

2.1 Offender Characteristics

This study attempts to identify spatial relationships between residence locations of convicted offenders and crime locations. Relevant literature was consulted to better understand spatial characteristics of offenders.

The body of knowledge regarding the subject of spatial characteristics between offenders and their target crime location, or Criminal Profiling, focuses primarily on the characteristics and understanding of violent predatory offenders. The focus is logical because this type of offender is a greater threat to society than other types of offenders. While it is the assumption of this study that this type of offender would not be sentenced under the AB 109 provision, the body was consulted with this assumption in mind to identify the spatial range of offenders.

In a survey of serial killers by Maurice Godwin, and David Canter, the average distance an offender traveled to "abduct the victims" was 1.45 miles with a standard deviation of 1.25 (Godwin & Canter 1997). This identifies that violent predatory offenders will offend close to their sphere of activity.

D. Kim Rossmo outlines a geographic profiling distance decay function that can be used to predict the "Offender's Residence" (Serial Killers) based on the number of Crime locations within an area (Rossmo, 1997). The inverse of this function indicates that an Offender will likely commit Crime near their place of residence.

In addition to Rossmo, many authors have noted that offenders are more likely to operate near areas that are familiar to them, such as their residence or place of employment (Brantingham and Brantingham, 1981; Godwin & Canter, 1997; Rhodes and Conly, 1981; Rossmo, 1997). As an example, violent predatory offenders or rapists are likely to operate very

close to their residence, within an average distance of 1.25 miles (Godwin & Canter, 1997). In contrast, robbers operate within an average of 2.10 miles and burglars operate within an average of 1.62 miles (Brantingham and Brantingham, 1981).

It is interesting to note that while the majority of the work regarding criminal profiling has been focused primarily on violent predatory offenders. Brantingham and Brantingham studied all types of offenders and their sphere of influence, noting the mean center of burglaries and robberies.

The body of knowledge on criminal profiling suggests that an offender will likely commit an offense near their residence. With this assumption this study attempts to find a correlation between crime rate increase, or Census Tracts that exhibited an increase in crime rates, and the residence locations of AB 109 offenders. The assumption being: if Census Tracts where crime increased are correlated with AB 109 offenders, a relationship between AB 109 and increased crime rates likely exists.

2.2 Recidivism

The literature suggests that offenders will likely commit offenses near their place of residence. To further determine the risk of changing the supervision type of convicted offenders, the literature was consulted on the subject of recidivism.

Recidivism can also be thought of as "reoffending" or a person's tendency toward criminal behavior after being released from a supervised sentence (Beard et al, 2013 pp. 5). This measure is significant as it can potentially gauge the effectiveness of certain institutions or programs on rehabilitating criminal behavior.

Recidivism rates in the United States are problematic and suggest offenders are likely to commit a new offense when released from prison. A report studying two thirds of offenders in

the United States noted a recidivism rate of 67.5% for those released in 1994 and 62.5% for those released in 1983; averaging the values the overall recidivism rate in the United States in 65% within three years of "release" (Langan and Levin, 2002 pp. 1). The report further found those who serve the longest sentences, "61 months or more," experienced a "significantly lower" recidivism rate of 54.2% (Langan and Levin, 2002 pp. 11). "Recidivism" rates calculated in the report include new convictions as well as arrests (Langan and Levin, 2002 pp. 1).

Research comparing recidivism rates of California offenders pre and post AB 109 suggest similar results. The year preceding AB 109 experienced 58.9% recidivism and the year following experienced 56.2% recidivism (Beard et al, 2013).

Recidivism is not only a problem in the United States, but in other countries as well, suggesting a global phenomenon. An article by Ignacio Munyo and Martín A. Rossi, studying recidivism on the day of release in Uruguay, found for every "four" offenders "released," one additional "reported crime" is expected (Munvo and Rossi, 2015 pp. 89). Additionally, the article found recidivism rates are similar, between 58 – 60%, in the "Netherlands," and "England and Wales" (Munvo and Rossi, 2015 pp. 81).

The literature suggests a high likelihood, 65% in the United States, offenders released from prison will commit a new offense, or be arrested, within three years of release. This is significant as it represents almost two thirds of offenders released from prison.

2.3 Crime Analysis

The subject of crime analysis was studied in depth in an effort to better understand the best methods used in the field. The opinions and methods of multiple articles were studied and are included below.

Temporal considerations are vital in determining the dataset that will be used in a crime

study. Rebecca Paynich, editor, from the International Association of Crime Analysts, notes when detecting "high crime areas" the analyst must determine the temporal range of the data (International Association of Crime Analysts, 2013, pp. 11). This suggests the temporal range of any Crime Analysis should be determined by the analyst. Careful consideration was taken when selecting the temporal time frame for this research. Trends needed to be established in order for new patterns to be identified.

In addition to the work noted above, an example was taken from an analysis conducted on a police operation in Philadelphia. The goal of the analysis was to determine the results of "Operation Safe Streets," a tactical operation performed by the Philadelphia Police Department in an effort to reduce "violent and "drug crimes" (Lawton et al. 2005 pp. 433). The analysis was conducted using approximately two years of data, 20 months, which was obtained from the Philadelphia police department (Lawton et al. 2005).

Using the methods presented in the "Operation Safe Streets" analysis, two year periods were determined to be the optimal temporal unit to capture data regarding a crime trend. As AB 109 took effect on 1 October 2011, the two year periods used to study crime trends related to the implementation of the law were separated into 1 October – 30 September 365 day (one year) units.

As a baseline for crime analysis, it is expected that areas with a higher population density will experience a higher rate of crime (Harries, 2006; Brandmüller and Önnerfors, 2011). As the body of work on the subject of crime analysis expects areas with higher population density to experience higher rates of crime, a strategy was developed for this research to overcome this obstacle. The crime points data were normalized to best determine crime trends over the entire county; offense counts were divided by population counts to determine crimes rates, or the

number of crime events, per number of people; methods on how crime rates were calculated are found in Chapter 3.

It is common knowledge that crimes committed in any jurisdiction vary from low level misdemeanors to serious felony violent crimes. In order to differentiate crimes for the study literature was consulted to determine the best method for categorizing crime types. The National Incident Based Reporting System or NIBRS categorizes multiple offenses into 3 categories: "Crimes Against Persons… Property… and Society" (LESS and CSMU, 2013, pp. 13). As part of this analysis, some of the cohorts studied consisted of crime counts divided into the NIBRS categories and counted. As other authors have studied typical crime groups such as NIBRS categories, this study will also investigate those crime types. Section *4.1 Descriptive Statistics* contains counts of Incidents Categorized under NIBRS categories.

In addition to the division of crime types, an investigation on factors that influence crime was also completed. The Federal Bureau of Investigation, or FBI, has published a list of factors that "Historically" have influenced crime rates such as "Modes of transportation and highway system" and "Economic conditions, including median income, poverty level, and job availability" (Federal Bureau of Investigation, 2006). These factors including others were considered when determining variables to include in this analysis. While it is noted that many different factors, including those published by the FBI, affect crime rates, only some of these factors are considered in this study. The availability and complexity of data, as well as the complexity of the analysis related to equifinality of the model were considered when determining the variables included in the analysis.

2.4 The Modifiable Areal Unit Problem or MAUP

As this study involves the comparison of aggregated units with regression analysis to determine if a correlation exists, there will no doubt be affects from the Modifiable Areal Unit Problem or MAUP. As such, a discussion of the MAUP and its effects on this study follow.

To begin the discussion, this study first attempts to describe the MAUP. The *Encyclopedia of Geographic Information Science* contains a very good definition of the MAUP written by Martin Charlton. Charlton defines the MAUP "as [a]… *scaling* and *aggregation* (or *zoning*) problem… [where] the number of areal units in a given study region affects the outcome of an analysis [or where there can be]… many different ways in which a study region can be partitioned into the same number of areal units" (Charlton, 2008, pp. 289). Meaning if 10 events were observed, a relationship established from this original set of data would differ from that of a relationship of the same 10 observed events, aggregated into two polygons. Additionally the first and second observation of the 10 events would further differ if the two polygons were aggregated further, creating four polygons.

Notice in Figure 3 when the un-aggregated data is aggregated into polygons the number of events in each polygon begins to change with each transformation; starting at 10 originally and receding all the way down to zero in one of the polygons as the original data was divided into four polygons. The MAUP creates a significant problem, because though the manipulation of aggregate units, the researcher can essentially create the correlation outcome desired or a stronger correlation simply by re-aggregating the study data. O'Sullivan and Unwin highlight this problem by noting that "if the spatial units in a particular study were specified differently, we might observe very different patterns and relationships" (O'Sullivan and Unwin, 2010, pp. 37).

The MAUP is especially relevant to this study due to the nature in which some of the data were obtained. For example, as noted in Section 3.2, offender location data was obtained aggregated to Zip code polygons, with some Zip Codes only containing 1 offender. The aggregation creates an issue conceptually wherein the offender could reside at any area in the Zip Code, but is counted with equal weight throughout the polygon. This has the potential to increase a positive or negative correlation between crime rates and AB 109 offenders.

This problem, is just that, a major problem with spatial data that is aggregated into larger spatial units. Few solutions exist for this problem, however one author, Openshaw contends that to solve the problem, research should consist of creating and exploring many "hypotheses" and explaining why such variance in the correlation results exist (Openshaw, 1983, pp. 37). This is a novel approach and an interesting solution to a very prevalent issue. This however has not caused the solution to be widespread; as O'Sullivan and Unwin point out, "perhaps because of the
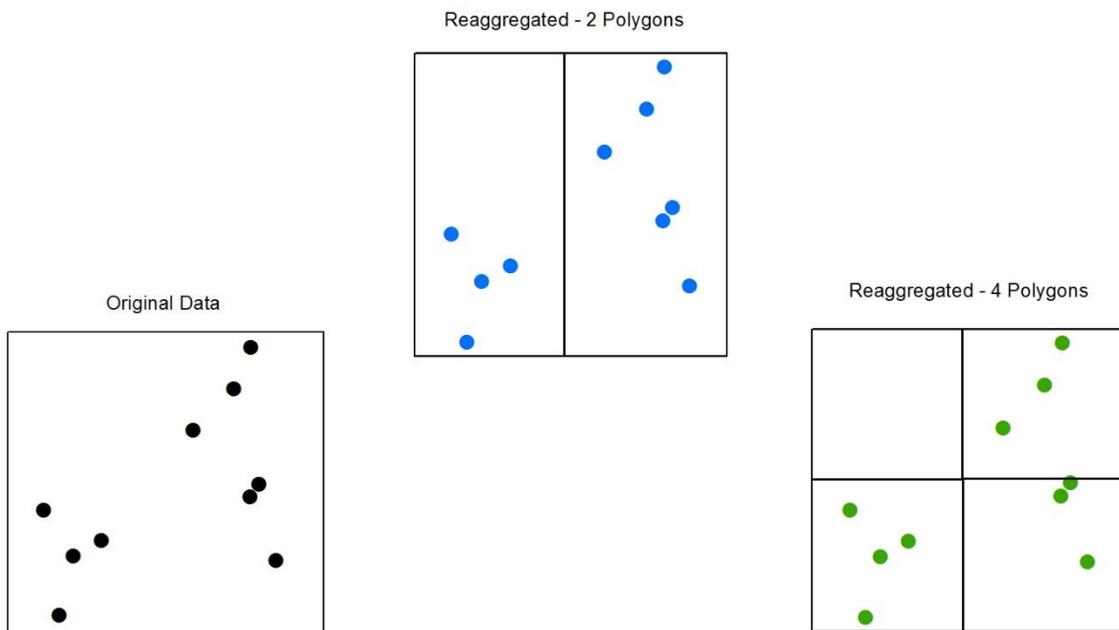
Figure 3: An Illustration of the MAUP and how Re-aggregation can affect Results

computational complexities and the implicit requirement for the very detailed individual-level data, this idea has not been widely taken up" (O'Sullivan and Unwin, 2010, pp. 38).

Although O'Sullivan and Unwin note that Openshaw's theory "has not been widely taken up," they do however offer guidance to dealing with the MAUP when examining "point pattern[s]" (O'Sullivan and Unwin, 2010, pp. 122). Specifically, among other factors for analysis, they suggest that a "study area should be objectively determined… [and] be independent of the pattern of events… it might be given by the borders of a country, shoreline of an island, or edge of a forest" (O'Sullivan and Unwin, 2010, pp. 122). This is an interesting note, as the MAUP is attempted to be solved, at least partially, by using natural or man-made barriers to end a continuous surface. This study, attempts to abide by this suggestion, at least partially, to mitigate the effects of the MAUP on the study results.

Chapter 3 Methods and Data

3.1 Study Area and Software

While other studies and reports mentioned previously have studied crime and recidivism rates by

establishing relationships by numbers alone, this study attempts to establish relationships using

numbers and spatial relationships.

As AB 109 represents a large shift in the way that criminal offenders are sentenced and

supervised, this paper studies the effect of the new law on crime rates in San Diego County.

Other counties were considered and debated for this study, however among other factors briefly

stated in the Introduction, the availability of data was a key factor in selecting the study area. As

it is the case in most spatial studies conducted by students in academic programs the availability

of quality data is severely restricted or carries a high price.

To accomplish this task, this study utilized ESRI's *ArcGIS Desktop* platform as well as

The Omega Group's *CrimeView Desktop* Software. The *AcrGIS desktop* platform provides a

robust platform complete with a full suite of tools that enable geographic analysis. In addition to

ArcGIS, *CrimeView Desktop*, a proprietary extension, which runs inside of ArcGIS, provides

extra analysis tools that are specifically designed for crime analysis. IBM *SPSS* and SAS institute

JMP software were also used.

3.2 Data Sources

Taking into account the literature review of crime analysis techniques discussed in Section 2.2,

the relevant data for this study was determined to be crime point data, a polygon layer containing

counts of offenders being supervised under the AB 109 provision and population counts to

normalize the data. Other population data, such as poverty status, income status and marital

status, was desired to provide variables for the spatial regression analysis model used in this study (discussed in greater detail below).

The initial data acquired for the study consisted of a point data layer that contained the locations of crimes in San Diego County from January 1, 2007 to December 31, 2012 and April 1-31, 2013. This large crime point dataset was obtained from a data portal website, the San Diego Regional Data Library, located at "http://data.sandiegodata.org/dataset/clarinova_com-crime-incidents-casnd-7ba4-extract." This dataset provided a majority of the crime data needed for the study, however supplemental data was needed to complete the 2013 year.

To supplement the initial crime dataset, multiple 180 day comma separated value, or CSV, files, containing locations of crimes, were acquired from the SANDAG website for the missing months of 2013. This data was used to fill in the gaps of the missing months of the initial crime points dataset that had been gathered.

Table 1: Total Incidents and Rates per Year (1 October-30 September)

Year	Count	Rate (per 1000)
2007-08	168,266	54.36
2008-09	154,460	49.90
2009-10	147,549	47.67
2010-11	134,983	43.61
2011-12	130,570	42.18
2012-13	135,204	43.68
Total	871,032	281.40

As a basis for analysis, a year was calculated as increments between October 1st and September 30th. As AB 109 took effect on 1 October 2011, years were divided up in this fashion to capture pre and post AB 109 trends more effectively. Other studies evaluating AB 109 have separated temporal periods in this fashion (Beard et al, 2013). A total of 871,032 incidents were

observed from the temporal range of the data; the results of initial data counts are visible in Table 1.

The temporal resolution of the Crime data set is 6 years, or from 1 October 2007 to 30 September 2013. As stated above in Chapter *2.2 Crime Analysis,* the goal of this research was to gather two year crime point datasets, one on each side of the AB 109 implementation date, pre and post, to successfully establish crime trends. In addition to the primary datasets gathered for the study, an extra two years of data were obtained to further describe crime patterns and trends in the study region.

With the crime data gathered, it was necessary to supplement the data with additional datasets to explain patterns and trends in the data. As noted above in Section 2.2, criminal offenders usually operate within close proximity to their residence. To simulate this effect on AB 109 crime rates, it was determined the location of offenders serving probation time under the AB 109 statute should be included in the analysis. Including this data enabled the evaluation of the relationship between, at least some, persons convicted and sentenced under the AB 109 provision and the change in crime rates.

Table 2: 2013 Probation Totals

Type	Totals
Formal	6,624
PRCS	3,807
MS	613
Total	11,044

The offender residence locations were obtained as a result of a data request to the San Diego County Probation department; multiple tables containing counts of probationers by Zip Code were obtained. These tables were received in Excel format with counts of probationers, or offenders, per zip code. Table 2 displays probation data totals from the 2013 year; the categories

of probation are as follows: the "Formal" count could contain AB 109 offenders sentenced to a full felony probation sentence as well as offenders already serving a probation sentence before the passage of AB 109, "PCRS" or "Post-Release Community Supervision" contains counts of offenders released from prison after serving an AB 109 type offense, and "MS" or "Mandatory Supervision" contains counts of offenders serving probation after a "split sentence" as part of AB 109 sentencing (Californians for Safety and Justice, 2013). Because the formal count of offenders contains AB 109 and other offenders, only PCRS and MS counts of offenders were included as residence locations for AB 109 offenders.

Population data was gathered for San Diego County from the U.S. Census Bureau. Census geography was downloaded in Census Tracts and Zip Codes for San Diego County from the U.S. Census website. The corresponding data tables, containing population counts, were also downloaded from the Census' *American Fact Finder* website; the data tables were then linked to polygons and the result was two population layers, Census Tracts and Zip Codes, containing total population counts for the respective polygon features with data from the 2010 Census.

In addition to population data, additional variable data for the analysis was obtained from the Census Bureau. Data tables gathered were: Educational Attainment, Employment Status, Marital Status, Poverty Status, Median Household Income, Work Status, and Household and Families. These sources were obtained in table format from the 2010 Census and 2013 ACS Census counts. Both 2010 and 2013 Census data tables were tied to the 2010 polygon layer noted above. The requirement for these data variables was determined using the FBI's "Variables Affecting Crime" webpage (Federal Bureau of Investigation, 2006). A further explanation of the social variables obtained from the Census Bureau is contained in Appendix A.

In addition to the explanatory variables identified by the FBI above, when performing initial regression analysis, it was noted that a variable might be missing. After mapping residuals it was noted that over and under estimated tracts were clustered around the interstates in the area. In an attempt to compensate for the over and under estimation, a distance, in miles, from the freeway was calculated and added as an explanatory variable.

In connection with the relevant study data, multiple geography point, line and polygon layers were gathered from SANDAG for cartography and analysis purposes. These layers include streets and natural features such as lakes and streams.

3.3 Data Processing

While the majority of the datasets acquired for this study were obtained in usable GIS formats, a portion of data needed to be processed in order to be used within the ESRI *ArcGIS* platform. The data processing completed and data processing methods are listed below.

To fill gaps in the initial crime points dataset's 2013 year, and complete the overall Crime Dataset, two CSV files were gathered from the SANDAG website at: *http://www.sandag.org/index.asp?subclassid=21&fuseaction=home.subclasshome*. These tables contained multiple fields including the offense date, charge description and address generalized to the 100 block; a sample block of records from one of the tables is contained in Figure 4. A table in this form contains a wealth of valuable information, however heavy processing is necessary to transform the table into a usable GIS format. To transform the tables into a usable GIS point layer the following steps were performed:

- CSV tables were appended using date range.
- "Block" or "Blk" was removed from address field with the Field Calculate tool
- The Omega Group's Import Wizard Data processing tool was used to:

- o   Clean or replace bad values or inconsistencies in the data.

- o   Calculate Date and Time fields into YYYYMMDD and HHMM format.

- o   Geocode data with multiple address locators.

- Records not automatically geocoded were reviewed by hand and compared against street centerline source data. Remaining records were geocoded to the closest address number found in the street centerline range. For example; "100 Block Main St" would have attempted to geocode to "100 Main St," and "125 Main St" progressively provided there was not a match within the street centerline data for the original attempt of "100 Main St."

- Individual "Charge Descriptions" were grouped into Crime Types to match the initial crime points dataset using comparisons.

- Data was appended into the primary dataset for ease of analysis.

Due to the original 100 block format of the CSV table addresses, locations were approximated by geocoding to the numeric derivative of the 100 block address; for example "100 Block Main St" would have attempted to geocode to "100 Main St" on the first pass, and "125 Main St" progressively provided the original address was not matched. This process of estimating the matching address from street centerline data was repeated until all records, or as many that could be matched with a good estimation, were matched.

agency	Charge_Description_Orig	activityDate	BLOCK_ADDRESS	ZipCode	community
ESCONDIDO	CARRY CONCEALED DIRK OR DA	7/1/2013 23:16	E WASHINGTON AVENUE / N FIG STREET		ESCONDIDO
ESCONDIDO	DISORDERLY CONDUCT: ALCOH	7/2/2013 12:30	1600 E BLOCK WASHINGTON AVENUE	92027	ESCONDIDO
ESCONDIDO	MINOR POSSESS ALCOHOL	7/4/2013 20:20	300 N BLOCK BROADWAY		ESCONDIDO
ESCONDIDO	POSSESS CONTROLLED SUBSTAN	7/4/2013 20:20	300 N BLOCK BROADWAY		ESCONDIDO
ESCONDIDO	ALCOHOL RELATED	7/5/2013 18:50	WAVERLY PLACE / CLARK STREET		ESCONDIDO
ESCONDIDO	ALCOHOL RELATED	7/5/2013 18:50	WAVERLY PLACE / CLARK STREET		ESCONDIDO
LA MESA	USE ANOTHER PERSONAL IDENT	7/29/2013 22:00	7600 BLOCK NORMAL AVENUE	91941	LA MESA
LA MESA	BATTERY ON PERSON	7/16/2013 14:00	8800 BLOCK FLETCHER PARKWAY	91942	LA MESA
ESCONDIDO	BURGLARY/UNSPECIFIED	8/6/2013 10:00	300 W BLOCK EL NORTE PARKWAY	92026	ESCONDIDO
SHERIFF	USE/UNDER INFL OF CONTROLL	7/21/2013 12:05	N MAIN AVENUE / E IVY STREET	92028	FALLBROOK
OCEANSIDE	DRUNK IN PUBLIC: ALCOHOL, DI	11/26/2013 17:45	600 BLOCK DOUGLAS DRIVE	92058	OCEANSIDE
ESCONDIDO	USE ANOTHER PERSONAL IDENT	8/17/2013 0:01	500 W BLOCK EL NORTE PARKWAY	92026	ESCONDIDO
ESCONDIDO	GRAND THEFT:MONEY/LABOR/F	8/19/2013 21:30	2100 BLOCK STANLEY WAY	92027	ESCONDIDO
ESCONDIDO	GET CREDIT/ETC OTHERS ID	8/20/2013 14:10	800 E BLOCK MISSION AVENUE	92025	ESCONDIDO
ESCONDIDO	TAKE VEHICLE W/O OWNER'S CO	8/19/2013 18:00	1900 BLOCK SUNSET DRIVE	92025	ESCONDIDO
ESCONDIDO	TAKE VEHICLE W/O OWNER'S CO	8/18/2013 13:50	1400 BLOCK VIEW POINTE AVENUE	92027	ESCONDIDO
ESCONDIDO	EXHIBIT DEADLY WEAPON (OTH	8/19/2013 13:58	800 N BLOCK FIG STREET	92026	ESCONDIDO
ESCONDIDO	TAKE VEHICLE W/O OWNER'S CO	8/19/2013 21:42	1200 BLOCK REMBRANDT GLEN	92026	ESCONDIDO
EL CAJON	DUI ALC/0.08 PERCENT (M)	8/4/2013 1:30	200 BLOCK JAMACHA ROAD	92019	EL CAJON
ESCONDIDO	TAKE VEHICLE W/O OWNER'S CO	8/20/2013 23:00	900 BLOCK HOWARD AVENUE	92029	ESCONDIDO
ESCONDIDO	PETTY THEFT	7/12/2013 12:00	1400 BLOCK OAK HILL DRIVE	92027	ESCONDIDO
ESCONDIDO	BURGLARY/UNSPECIFIED	7/19/2013 20:30	200 E BLOCK VIA RANCHO PARKWAY	92025	ESCONDIDO
ESCONDIDO	GRAND THEFT:MONEY/LABOR/F	8/23/2013 13:48	300 W BLOCK EL NORTE PARKWAY	92026	ESCONDIDO
SHERIFF	PETTY THEFT(All Other Larceny)	7/7/2013 21:45	30800 BLOCK OLD HIGHWAY 395	92026	ESCONDIDO U
ESCONDIDO	GET CREDIT/ETC OTHERS ID	8/20/2013 15:45	400 BLOCK DALE AVENUE	92026	ESCONDIDO
ESCONDIDO	PETTY THEFT	8/20/2013 16:00	1300 E BLOCK VALLEY PARKWAY	92027	ESCONDIDO
ESCONDIDO	VANDALISM (LESS THAN $400)	8/21/2013 1:43	3100 BLOCK SYCAMORE CREST PLACE	92027	ESCONDIDO

Figure 4: 2013 Crime Data in Native CSV Format

Probation counts by Zip Code were obtained in Microsoft Excel table format. Tables contained two counts of only AB 109 offenders per Zip Code; the "Mandatory Supervision" count and the "Post Release Community Supervision" count (Californians for Safety and Justice, 2013). Both probation types, "Mandatory Supervision" and "Post Release Community Supervision" are both new designations of probation types that were created for AB 109; "Post Release Community Supervision" is designated as the probation supervision of those released from State Prison after serving time for an AB 109 type offense. "Mandatory Supervision" is the designation of supervision after an offender is released from county "jail" on a "Split-Sentence" (Californians for Safety and Justice, 2013). Data was processed by joining the Probation tables to a Zip Code polygon table by the Zip Code field. Multiple polygon layers were created for each

year of probation data received. MS counts and PRCS counts were added together to attain a full count of AB 109 offenders per Zip Code. A sample block of records from the 2013 probation table can be found in Table 3.

Table 3: 2013 Probation Counts

ZIP CODE	FORMAL PROBATION	PRCS	MS
Blank	1234	957	131
92021	156	103	16
92024	34	11	5
92025	141	57	14
92026	84	51	16

3.4 Data Issues

The data collected for this study are very complete and robust, however a few data issues existed; a discussion of the various data issues follows.

First, the probation tables obtained are in very good condition, however, as displayed in Table 3, a record containing a "Blank" Zip Code corresponds with a count of offenders. Because no location information was tied to these counts they were not included in the study in an effort to preserve the spatial distribution of the data.

Second, the SANDAG website that allows for the download of Crime CSV files is based on a previous 180 day range. The data was gathered beyond the date range, omitting 8 days of data at the start of the 2013 year. The date range of the missing data is 2013-01-01 to 2013-01-09. As this date range represents 2.2% of a year the effect of the missing data on the study should be negligible.

3.5 Methods

With the aggregate of the information gathered, an extensive analysis was performed to determine if a relationship exists between residence locations of AB 109 offenders and crime rate increase across San Diego County. Other variables were also tested to in an attempt to provide alternative explanations for changes in crime rates. The assumptions and statistical methods used for the study follow.

ESRI*'s ArcGIS* software suite was used to perform the majority of the analyses as it provides very useful statistical tools. Tools provided by the *ArcGIS* platform are extensive and allow for many operations, including regression analysis and zonal statistics. In Addition to the tools provided with the *ArcGIS* platform, the analysis tools provided by the Omega Group's *CrimeView Desktop* software were used to perform analysis. *CrimeView Desktop* provides a full suite of tools that can be used to analyze crime including hot spot analysis and a *Crime Rate Generator*. IBM *SPSS* and SAS Institute *JMP* statistical programs were also used to analyze the data.

To begin the analysis, a major requirement of the data was to be divided into temporal periods and crime categories for comparison. An in depth procedure of how the data was divided follows.

The crime points dataset, or reported crimes in San Diego County, was first separated into two datasets for comparison; pre and post AB 109 temporal periods. Reported crimes, or crime points, from 1 October 2009 – 30 September 2011 was established as the pre AB 109 temporal period. Conversely reported crimes occurring between 1 October 2011 – 30 September 2013 was established as the post AB 109 temporal period for comparison. An additional two year period, 1 October 2007 – 30 September 2009, is included in descriptive statistics to offer

additional insight into crime trends in San Diego County during this period. It should be noted however that the main temporal periods studied immediately preceded and followed implementation of AB 109 (1 October 2009 – 30 September 2011 and 1 October 2011 – 30 September 2013).

In addition to dividing the reported crime events into two temporal periods, crimes were further divided into several categories for comparison to ascertain the effect of AB 109 on each crime category. Reported crime events were separated into the following cohorts:

- AB 109 categorized events

- Non AB 109 categorized events

- Crimes Against Property

- Crimes Against Society

- Crimes Against Persons

The cohorts categorized under NIBRS categories, "Crimes Against Persons… Society" and "Property," investigated previous claims of affected crime trends in California (LESS and CSMU, 2013, pp. 13; Beard et al, 2013; Lofstrom & Raphael, 2013). The cohorts comparing AB 109 offenses to non- AB 109 offenses, help to further study the crime trends occurring in California due to the new law.

As noted previously in this paper: it is expected that areas with a higher population density will experience a higher rate of crime (Brandmüller and Önnerfors, 2011; Harries, 2006). To normalize for this expectation a crime rate was determined by obtaining the number of crimes per 1000 persons for each Census Tract in San Diego County; the *CrimeView Desktop* software extension *Crime Rate Generator* and the *Spatial Join* and *Field Calculator* functions of *ArcGIS* were used to calculate crime rate numbers. Crime rates were generated by querying NIBRS

categories and groups classified as AB 109/Non AB 109 crime types, for 2 year periods to establish a control or a baseline for comparison. Crime rates for one of the temporal periods studied are displayed in Figure 5.

Figure 5: Property Crime Rates (Crimes per 1000 people) between 1 October 2011 and 30 September 2013 - Data Aggregated by Census Tract

Upon initial review of the Non AB 109 cohort, a box plot test was performed to determine if the distribution of the data was normal. Upon completion of the test outliers were determined to be present in the data more than 1.5 box plots away (Laerd Statistics, 2015). Some outliers, where the population was lower than 1000 persons, were removed to normalize the data. The outliers, where a larger number crimes than the total population are reported or if the

population for the census tract was lower than 1000, contained abnormally skewed crime rates. A total of 4 outliers were removed from the crime rate analysis to mitigate the effect of the outliers on the data. This however did not mitigate the effect of all the outliers; several outliers, many of them extreme outliers remained in the analysis. Because of the nature of the extreme outliers in the data, a "Wilcoxon signed-rank test" was performed on the cohorts to determine the statistical significance of the findings (Laerd Statistics, 2015).

In order to calculate, measure and normalize the data for population in San Diego County, crime rates were calculated for each census tract in the county. Crime rates for this study are defined as crimes per 1000 persons as displayed in the equation below (New Jersey State Police, 2015). Crime rates were calculated by dividing the total number of reported crimes in each census tract, by the population of the census tract and multiplying the result by 1000.

$$Crime\ Rate = (Reported\ Crime/Population) * 1000$$

Once crime rates were established, the difference was calculated between the control and the variable time periods, 1 October 2009 to 30 September 2011 being the control, and 1 October 2011 to 30 September 2013 being the variable. Having established the change in crime rates during the two year period, multiple analyses were performed to determine the significance, if any, of the relationship between the difference in crime rates and the populations of AB 109 designated offenders as well as other variables such as median household income and single parent households. An inferential statistical analysis and spatial analysis was performed on the data.

As noted above in Section 3.2 offender data was gathered and obtained in table form with counts of offenders aggregated by Zip Code. This presented a problem as polygons used

for population and other demographic data were aggregated by Census Tract and regression analysis cannot be performed between different areal units.

Operating under the assumption that the counts of probationers in each Zip code were evenly distributed throughout the polygon Zonal Statistics were used to re-aggregate the offender or probationer data to Census Tract polygons. The *Identify* and *Dissolve ArcGIS* tools and *Field Calculator* were used to perform this task. The *Identify* tool combined the Zip code and Census tract polygons to create a multitude of polygons by cutting polygons at each intersecting point. The new polygons contained the attributes of each original Census tract and Zip code polygon. After creating the polygons, the geometry, in square kilometers, of each new polygon was then calculated and the percentage of each new polygon comprising each individual Zip Code was calculated. The aerial percentage of each polygon was then multiplied by the offender count from the Zip Code it was created from. The new polygons were then dissolved into Census tract using the ID of each Census Tract. When dissolving, a sum of the offender counts was produced. The final result was a layer that contained an equal percentage of offenders per tract to the areal percentage of each Zip Code. Figure 6 illustrates the re-aggregation of offender data from Zip code polygons to Census tract polygons.

ZIP Code Probation Counts

- 0.00 - 2.00
- 3.00 - 9.00
- 10.00 - 17.00
- 18.00 - 23.00
- 24.00 - 31.00
- 32.00 - 39.00
- 40.00 - 54.00
- 55.00 - 81.00
- 82.00 - 120.00
- 121.00 - 223.00

Zip and Tract Intersect Counts

- 0.00 - 0.28
- 0.28 - 0.87
- 0.87 - 1.71
- 1.71 - 2.96
- 2.96 - 4.70
- 4.70 - 7.38
- 7.38 - 11.79
- 11.79 - 18.16
- 18.16 - 30.74
- 30.74 - 71.24

Census Tract Probation Counts

- 0.00 - 0.81
- 0.81 - 1.71
- 1.71 - 2.97
- 2.97 - 4.76
- 4.76 - 6.96
- 6.98 - 10.15
- 10.15 - 14.19
- 14.19 - 20.43
- 20.43 - 31.77
- 31.77 - 95.97

0 10 20 40
Miles

NORTH
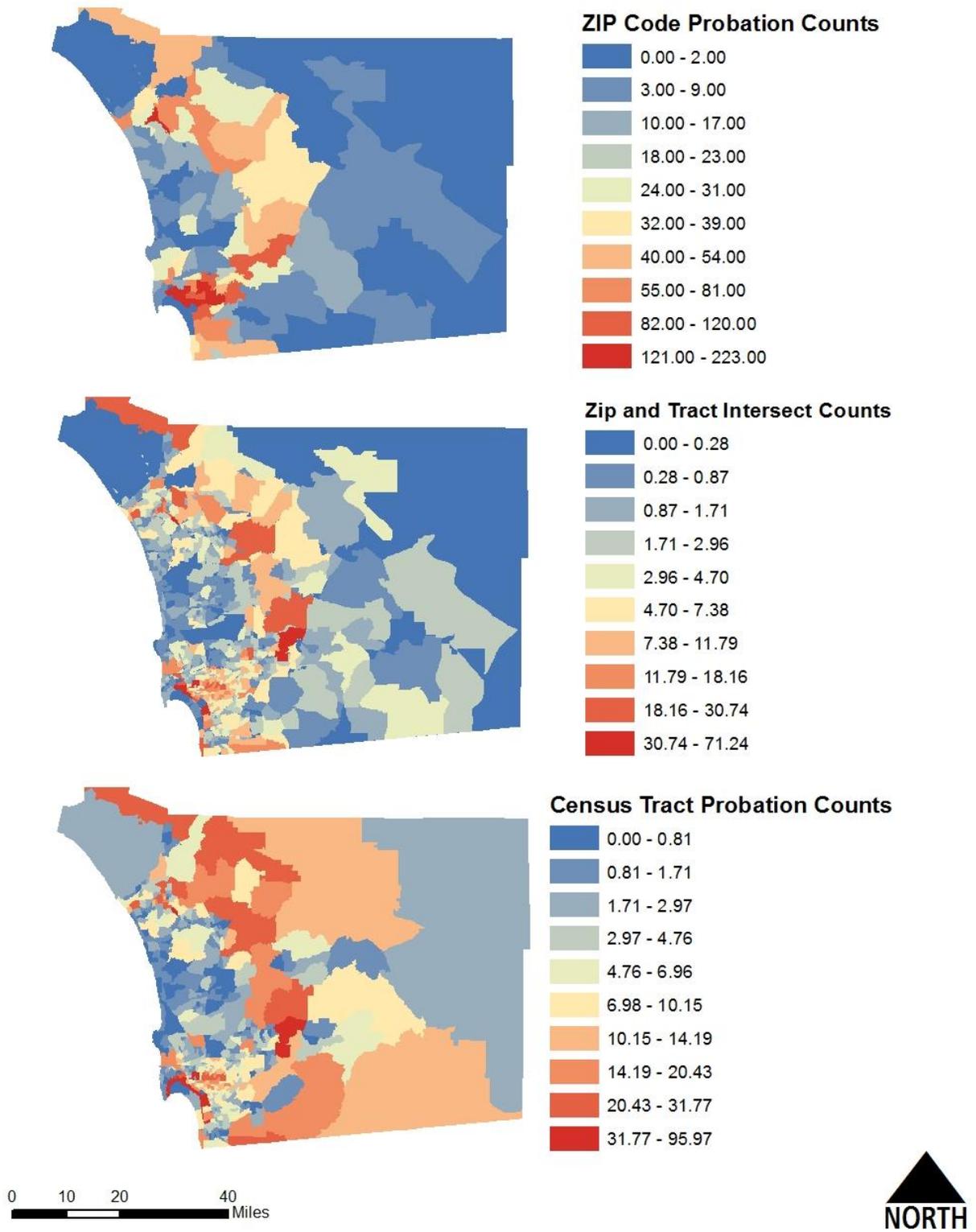
Figure 6: Re-Aggregation of Offender Counts from Zip Codes to Census Tracts

30

This study used traditional and spatial statistics methods to analyze crime rate data at the census tract level. Traditional statistics methods were used to calculate the general trend of the data by calculating a median increase or decrease value and calculating probability. Spatial statistics used hot spot and regression analysis to determine the correlations between crime rates and variables studied.

To calculate the trend of crime rates in San Diego County during the studied temporal periods, *IBM SPSS* statistical tools were used. A Wilcoxon signed-rank test was performed on each crime category to determine the Z-score and probability of the cohort. In addition to the Wilcoxon signed-rank test, the median crime rate difference value was calculated to determine the direction of the trend; for example, an increase or decrease in crime rates.

As this study attempts to determine the spatial effects of offender residence locations and other variables to crime events, regression analysis was used to determine the extent of the relationship between the difference in crime rates during the period studied and the variables selected for the study. Regression analysis is a common statistical method and is seen in many scientific studies. This form of analysis was determined to be the most useful and descriptive statistic to calculate the correlation between the variables.

When considering performing any spatial analysis, including regression, it is important to note that spatial statistic assumptions are generally different than those of a traditional statistical analysis. Specifically, in traditional statistics methods, an underlying assumption of the data is that the "samples" or data collected for the study, "must be random," whereas spatial data carries the assumption of "spatial autocorrelation" (O'Sullivan and Unwin, 2010, pp. 34). Spatial autocorrelation carries the assumption that in geography, closer phenomena are likely to be

similar in characteristic, than distant phenomena in a spatial environment (O'Sullivan and

Unwin, 2010, pp. 34).

When considering using regression analysis, it is also important to note; while many GIS

questions ask "Where" events are occurring Regression analysis examines "Why" events are

occurring (Murak, 2015, pp. 3).

To ask *why,* as noted above, it is important to understand *where* events are occurring. To

this end, multiple analyses were performed on the crime rate data to answer the questions: *Are*

Crime Rates in San Diego increasing? If so, where? Which types of crime are increasing?

To answer these questions, hot spot maps were produced to determine areas where

statistically significant increases in crime had occurred. Once these areas were identified,

regression analysis was used to test the relationship between the independent and explanatory

variables in the hot spot. This method is covered in more detail later in this section.

The *ArcGIS* suite provides various tools to perform regression analysis. This study

utilized the *Ordinary Least Squares* tool to perform regression analysis. In addition to the

ArcGIS *OLS* tool, a statistical software program *JMP*, published by the SAS institute, was used

to help determine variables to include in the OLS analysis. These tools were used to analyze the

difference in crime rates from the NIBRS and AB 109/Non AB 109 categories.

Regression analysis is used to display a correlation, positive or negative. A correlation

can be thought of as a relationship between two variables. The independent variable for the

regression analysis in the study was the difference in crime rates between the temporal periods

studied. The explanatory variables examined were: the residence location of AB 109 offenders

serving probation in San Diego County during the 2013 year, Educational Attainment,

Employment Status, Marital Status, Poverty Status, Median Household Income, and Work

Status. The explanatory variables are explained in more detail in Appendix A. The data source of the explanatory variables as well as the independent variable can be found in Chapter 3.2.

The *Ordinary Least Squares* tool functions by providing useful data about the strength of and descriptive potential of each variable, as well as overall model strength. A few of the useful indicators supplied by the model follow: the "Variance Inflation Factor (VIF)" indicates "redundancy among explanatory variables," the "Joint F-Statistic and Joint Wald Statistic" indicate "overall model statistical significance," and the "Probability" aides in determining "Statistical Significance" of an "explanatory variable. (ESRI, 2013). All of these indicators and more were used in determining the strength of the relationship between explanatory variables and the difference in crime rates.

The *JMP* software platform provides a *Fit Model* tool to run step wise regression, among other functions. The *Fit Model* tool functions as follows: the type of analysis to be run is selected, a Y variable is selected, and multiple X variables can be selected. Once variables are selected, an automated step wise regression analysis can be performed, forward and backward. A minimum model fitness value can be selected to stop the step wise regression at that point; for example minimum AIC or BIC.

Step wise regression was performed using the crime rate difference as the Y variable and the explanatory variables, described above, as the X variables. The tool was run forward and backward to determine the best variables to use in the regression model. Minimum AIC and BIC values were considered when running the analysis. The results of step wise regression were used to perfect the spatial OLS models constructed as part of the study.

As it was more than likely that spatial autocorrelation was present in the data collected for this study, a widely used calculation, Moran's I, was used to determine the amount of

autocorrelation in the data after running regression analysis (O'Sullivan and Unwin, 2010). The *ArcGIS* "Spatial Autocorrelation (Moran's I)" tool was used to test the residuals of the regression analyses to determine the validity of the result (ESRI, 2013). An illustration of the Moran's I output and statistics can be found in Figure 7.
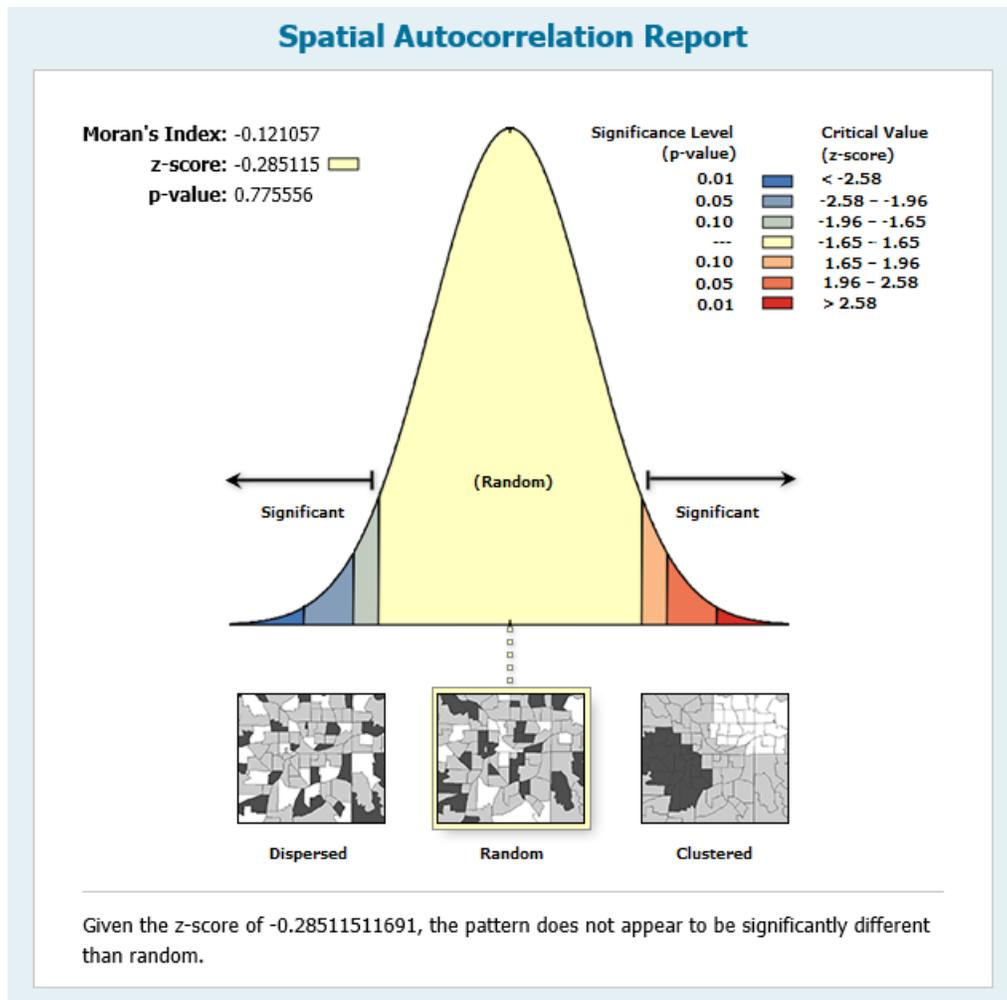
Figure 7: Example of Moran's I Tool Output Testing Autocorrelation of Residuals

Chapter 4 Results

4.1 Descriptive Statistics

After thorough data processing was performed on a majority of the data, an initial exploration, or descriptive statistical analysis of the data was conducted. The summary of the statistical analysis is described in detail below.

When comparing trends between the AB 109 categorized offenses and Non AB 109 categorized offenses, it was found that both cohorts saw a decrease in both overall incident counts and crime rates following the implementation of the law. The AB 109 Offense cohort experienced a 4.7% decrease between the two temporal periods studied. The Non AB 109 cohort experienced a larger decrease of 14.8% during the same period. Counts for both categories separated by year are displayed in Table 4. This observed decrease in crime rates between these two cohorts is interesting, particularly as the AB 109 group of crimes exhibited a decrease in crime rates during the period studied. As noted below, when crime types were further divided into NIBRS crime categories, two out of the three categories exhibited an overall increase.

Table 4: AB 109 Offenses vs Non AB 109 Offenses queried from 1 October to 30 September

Pre/Post AB 109	Time Period	AB 109 Offenses	Non AB 109 Offenses	Total Crimes
Pre AB 109	2009 - 2010	120,659 (81.8%)	26,897 (18.2%)	147,549
Pre AB 109	2010 - 2011	110,482 (82.9%)	24,504 (16.5%)	134,983
Post AB 109	2011-2012	108,622 (83.2%)	21,960 (16.8%)	130,570
Post AB 109	2012 -2013	111,760 (82.7%)	23,051 (17.0%)	135,204

Of the three NIBRS cohorts studied, Property Crime, is of particular interest to this study; as many authors have contended that property crime is rising due to AB 109 (Beard et al, 2013;

Lofstrom and Raphael, 2013). In contrast to the overall event count, and the AB 109 vs Non 109 cohorts, the NIBRS crime event datasets display different trends. When the dataset was further divided, trends in the data were much more pronounced. For example, the Crimes against Property category saw a decrease of 36,277 (-17.97%) events during the 2009-11 period. However an increase of 3,741 (+2.26%) occurred during the 2011-13 period, as compared to the 2009-11 period. Overall the property crime cohort exhibited a decrease of 32,536 (-16.12%) for the range of the data. However it is important to note that although property crime rates have decreased overall, they exhibited a rising trend during the last data period. This has the potential to be significant due to the large drop in crime rates from the previous period. Meaning, property crime was trending down sharply and has now experienced an increase immediately following the implementation of AB 109, reflecting the claims of previous studies.

Table 5: NIBRS Crime Category Counts for San Diego County - 1 Oct 2007- 30 Sep 2013

Period	Societal Crime	Personal Crime	Property Crime
2007-09	89,365	27,962	201,893
2009-11	89,444 (+0.09%)	24,129 (-13.71%)	165,616 (-17.97%)
2011-13	68,116 (-23.85%)	24,549 (+1.74%)	169,357 (+2.26%)

In stark contrast to the property crime cohort, the crimes against society, or societal crime, cohort exhibited almost no change, an increase of just 79 events (+0.09%) during the 2009-11 period, displayed in Table 5, indicating that the societal crime trend was steady leading up to the implementation of AB 109. In addition to the steady rate leading up to the implementation of AB 109, a sharp decrease of -21,328 events (-23.85%) during the 2011-13 period as compared to the previous period also sharply contrasts the property crime cohort.

In addition, Crimes against persons also remained relatively unchanged after a sharp drop from the 2007-09 period. During the 2009-11 period San Diego County saw a drop of 3833 Crimes against Persons events or a 13.71% decrease. In contrast, the 2011-13 period exhibited a much less pronounced change; an increase of 425 events (+1.7%) increase. Table 5 displays the event counts for Crimes against Persons.

As property crime was the only cohort that exhibited any type of significant increase during the temporal period following AB 109 implementation; and as an increase in crime rates is of the greatest concern to society, selected property crime types were studied in addition to the overall cohort.

THEFT/LARCENY

41311

38948

44670

incident Count

2007-09   2009-11   2011-13
Period
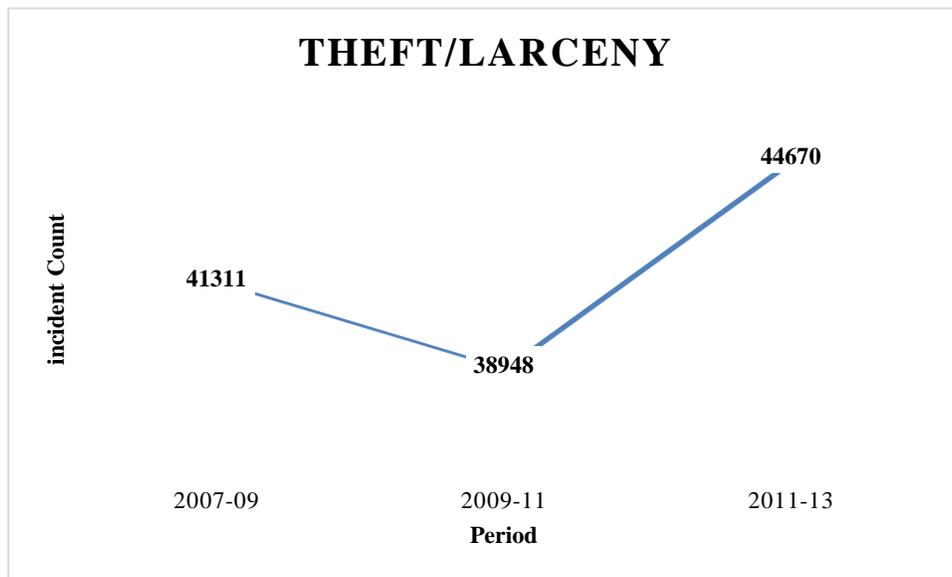
Figure 8: Theft/Larceny Trend (1 October - 30 September)

For example, thefts or larcenies were investigated more closely and revealed an interesting trend. The property crime cohort exhibited an overall decline during the temporal range studied, however thefts or larceny events exhibited a significant increase during the temporal range. The dataset displayed an initial decrease of 2,363 (-5.72%) events during the 2009-11 period as displayed in Figure 8. However thefts increased by 5,722 (14.69%) events

37

during the 2011-13 period as compared to the 2009-11 period and displayed a total increase of 3,359 (8.13%) during the temporal range of the study. The data from this cohort exhibits an interesting pattern, because although it follows the general pattern of property crimes, it exhibited a far greater increase immediately following the implementation of AB 109.

   In addition to the theft/larceny crime type, the burglary crime type of the property crime cohort was studied to further investigate trends. While not as dramatic, the burglary dataset exhibited a similar pattern to the theft/larceny dataset. As with larcenies burglaries decreased by 4,293 (-14.06%) events during the 2009-11 period. Again however, burglaries exhibited an increase of 5052 (+19.25%) during the 2011-13 period as compared to the previous period and
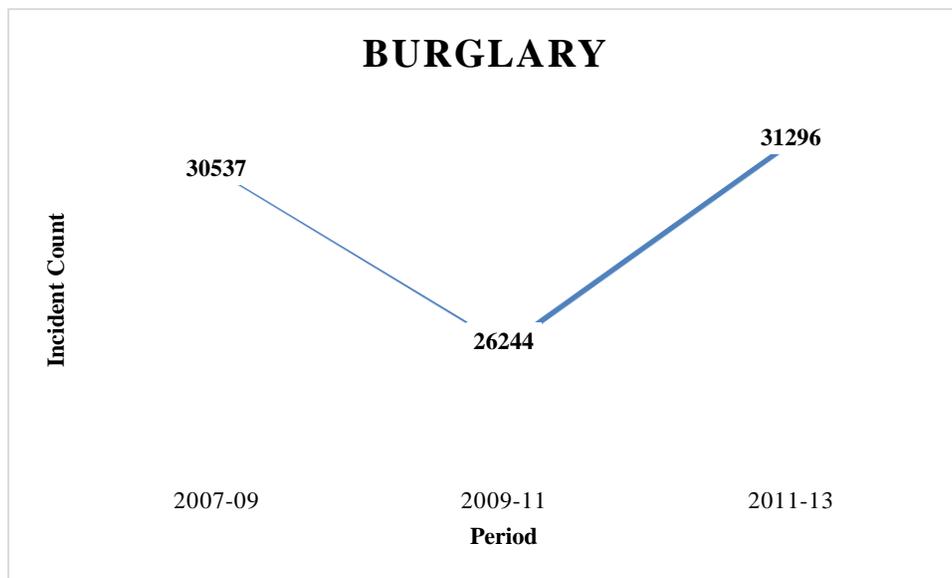
Figure 9: Burglary Trend (1 October - 30 September)

exhibited an overall increase of 759 (+2.49%) events during the temporal range of the data as displayed in Figure 9. As with theft/larceny, burglary followed the overall trend displayed by the property crime cohort, however exhibited the highest measurement at the end of the temporal range of the data, immediately following implementation of AB 109. These trends are troubling, because although the larger, more inclusive, property crime cohort exhibited a small increase at

the end of the temporal range, the final measurement was less than the beginning of the range. The trends of thefts, larcenies and burglaries indicate that hidden in the overall property crime cohort, some increased trends of theft and burglary were present in San Diego County during the range of the study.

While descriptive statistics show clearly that, as other studies have found, property crime in San Diego County has increased following the implementation of AB 109; it is important to use inferential statistics to determine if the trend on San Diego is likely found in other parts of California, as AB 109 is a state-wide statute. An inferential statistical analysis of the data follows.

As stated previously, the crime points dataset, or reported crimes in San Diego County, were divided up into two temporal periods for comparison Pre and post AB 109. Reported Crimes, or crime points, from 1 October 2009 – 30 September 2011 was established as the pre AB 109 temporal period. Reported Crimes, or crime points, from 1 October 2011 – 30 September 2013 was established as the post AB 109 temporal period for comparison.

Data was further divided into different crime groupings for analysis. First the data was grouped into crimes that would fall under the new AB 109 classification, and crimes that are excluded from the new AB 109 classification (Byers, 2011; County of Los Angeles Probation Department, 2015; Couzens, 2013; Harris and Donaldson, 2013). FBI classifications of "Crimes Against:" "Persons, Property" and "Society" were also compared.

4.1.1. Non AB 109 Categorized Offenses

In total, 623 census tracts in San Diego County were included in the analysis. Of the 623 census tracts studied, 427 experienced a decrease in crime rates during the subsequent period following the implementation of AB 109, 17 experienced no change, and 179 experienced an

increase in crime rates. The results of the Wilcoxon signed-rank test, displayed in Table 7, found

a statistically significant median decrease in crime rates, -1.6, during the temporal period studied,

z=-12.213, p < 0.0005. The small P value indicates that the probability of the null hypothesis,

AB 109 had no effect on crime rates, occurring, is less than 1%, indicating statistical

significance.

Table 6: Degree of Change in Crime Rates from the Crime Categories Studied

| Category	Median	Maximum Increase	Maximum Decrease
Non AB 109	-1.6	45.02	-43.40
AB 109	-2.0	175.55	-241.92
Property	0.7	130.79	-124.72
Societal	-3.5	71.14	-240.34
Personal	-0.1	14.79	-18.47

The median value of -1.6 exhibited by the Non AB 109 category, indicates that crimes in

this grouping decreased by an average of 1.6 events per 1000 persons in each census tract. As

displayed by the data, and Table 6, this category of crimes displayed an overall decrease between

the control and variable temporal periods. It appears from the initial statistical analysis, that the

temporal period coinciding with the implementation of AB 109 experienced a decrease in crimes

that are not punishable under the new AB 109 statue.

Table 7: Wilcoxon Signed Rank Test of Non AB 109 Offenses Results

Observations (N)	623
Increase Exhibited	179
Decrease Exhibited	427
No Change	17
Z Score	12.213
Probability	< 0.0005

During the period, as stated above, 427 (68.54%) tracts experienced a decrease in crime rates during the subsequent period following the implementation of AB 109, as exhibited in in Table 9 below, 17 (2.73%) experienced no change, and 179 (28.73%) experienced an increase in crime rates. The maximum rate increase of this cohort was 45.02 in Census Tract 89.02, and the maximum decrease was -43.40 in Census Tract 183. The variance of the data, represented by standard deviations, is displayed in Figure 10.

These Crimes are basically the opposite of the AB 109 categorized crimes and hence include the "Violent, Serious and Sexual" crime not specified by the law (Californians for Safety and Justice, 2013). These crimes include murder, rape, robbery, etc.; the median decrease in
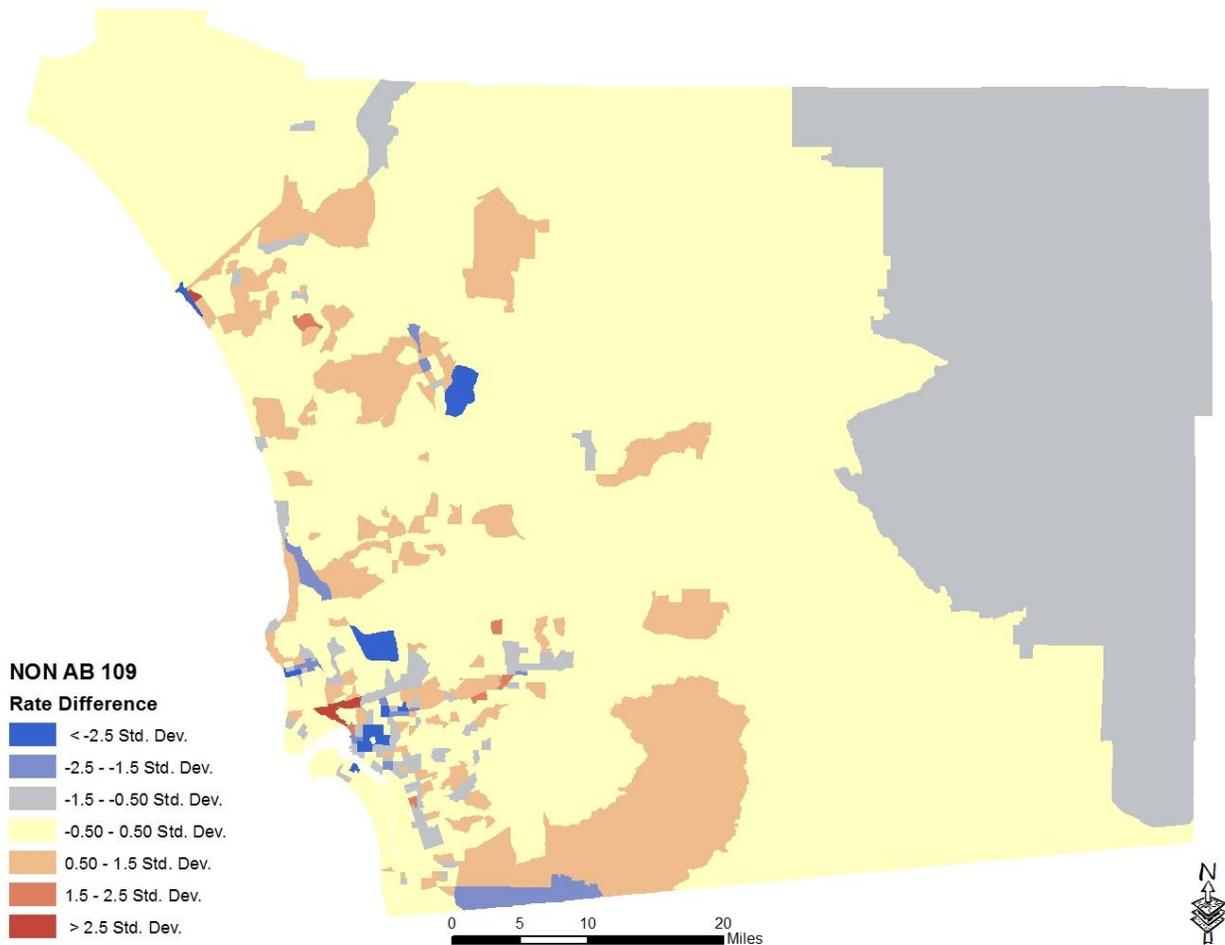
Figure 10: Variance of Non AB 109 Crime Rate Difference Values

crime rates related to this group, is a positive as the crimes listed above are especially heinous and are detrimental to society.

4.1.2. AB 109 Categorized Offenses

As stated above with Non AB 109 offenses, in total, 623 census tracts in San Diego County were included in the analysis of AB 109 Categorized Offenses. Of the 623 census tracts studied, 351 experienced a decrease in crime rates during the subsequent period following the implementation of AB 109, 7 experienced no change, and 265 experienced an increase in crime rates. The results of the Wilcoxon signed-rank test, displayed in Table 8, indicated a statistically significant median decrease in crime rates of 2.0 events per 1000 people during the temporal period studied, $z = -4.694$, $p < .0005$. Again, the small P value indicates the probability of the null hypothesis, AB 109 had no effect on crime rates, occurring, is less than 1%, indicating statistical significance.

Table 8: Wilcoxon Signed Rank Test of AB 109 Offenses Results

Observations (N)	623
Increase Exhibited	265
Decrease Exhibited	351
No Change	7
Z Score	-4.694
Probability	< 0.0005

The median value of -2.0 exhibited by the AB 109 category, indicates that crimes in this grouping decreased by an average of 2.0 in each census tract. The maximum rate increase of this cohort was 175.55, and the maximum decrease was -241.92, as displayed in Table 6. As

displayed by the data, this category of crimes displayed an overall decrease between the control and variable temporal periods.

As noted below in Table 9, 351 (56.34%) Census Tracts experienced a decrease in AB 109 categorized crime rates, 7 (1.12%) experienced no change, and 265 (42.54%) experienced an increase in crime rates. These numbers indicate that slightly over half, 50 percent, of Census Tracts in San Diego County experienced a decrease in crime rates for this category. The variance of the data, represented by standard deviations, is displayed in Figure 11.

These crimes include all "non-serious, nonviolent or non-sex" felonies or crimes
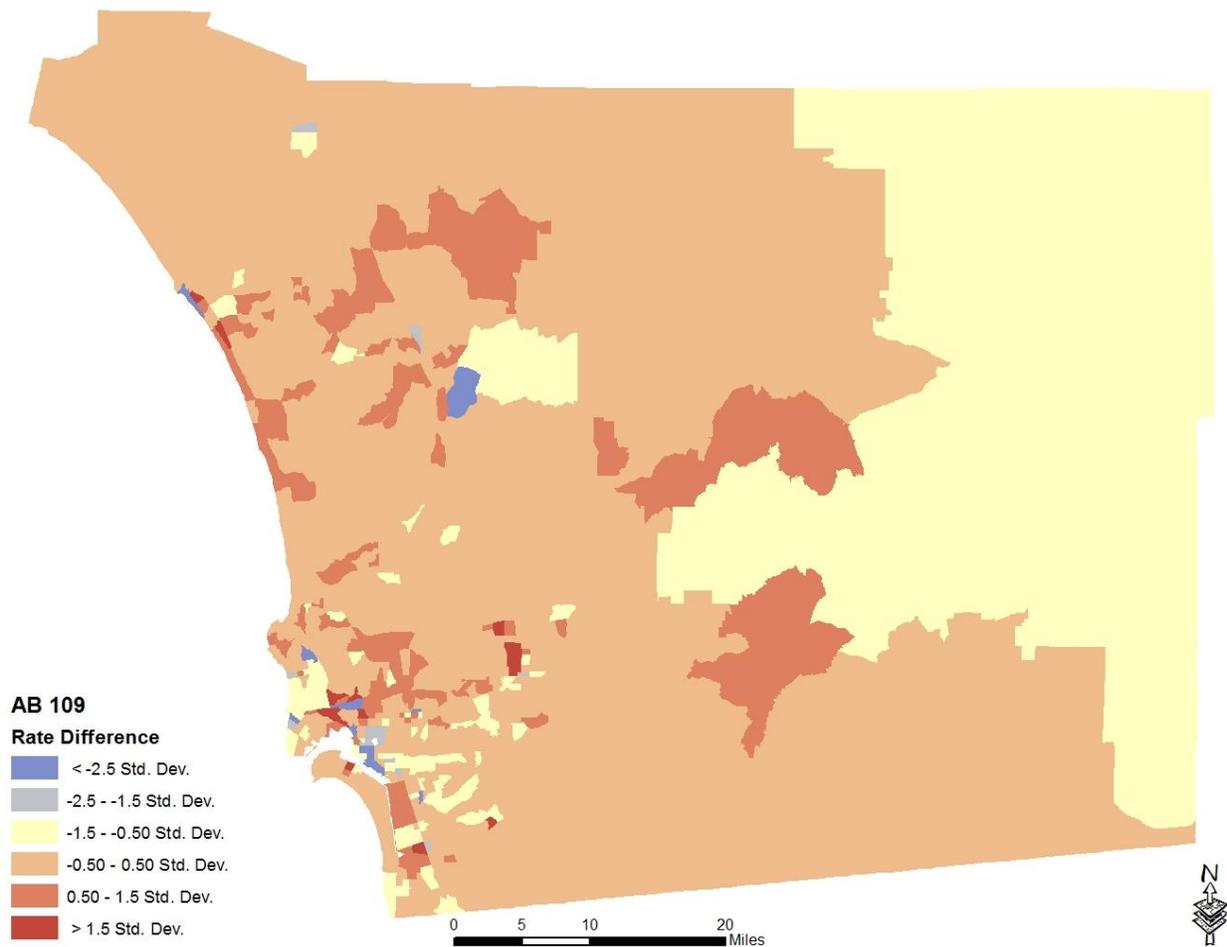
Figure 11: Variance of AB 109 Category Crime Rate Difference Values

including vandalism, vehicle break-in/theft, vehicle burglaries, and controlled substance

possession (Californians for Safety and Justice, 2013). The -2.0 median rate change, representing 56.34% of the Census Tracts in the county, related to this category is quite significant because it represents a wide range of crimes.

4.1.3. Crimes Against Property

As with the previous cohorts, in total, 623 census tracts in San Diego County were included in the analysis of property crime offenses. Of the 623 census tracts studied, 293 experienced a decrease in crime rates during the subsequent period following the implementation of AB 109, 7 experienced no change, and 323 experienced an increase in crime rates. The results of the Wilcoxon signed-rank test, displayed in Table 10, indicate a statistically significant median increase in crime rates of 0.7 events per 1000 people during the temporal period studied, $z=2.264$, $p = 0.024$. Property Crime was the only cohort studied that exhibited any relative increase in crime rates. The small P value indicates the probability of the null hypothesis, AB 109 had no effect on crime rates, occurring, is less than 1%, indicating statistical significance.

Table 9: Crime Rate Change between Studied Temporal Periods

| Category	Count of Tracts Displaying Increase	Count of Tracts Displaying Decrease	Count of Tracts Displaying No Change
Non AB 109	179 (28.73%)	427 (68.54%)	17 (2.73%)
AB 109	265 (42.54%)	351 (56.34%)	7 (1.12%)
Property	323 (51.85%)	293 (47.03%)	7 (1.12%)
Societal	127 (20.38%)	488 (78.33%)	8 (1.28%)
Personal	260 (41.73%)	318 (51.04%)	45 (7.22%)

The median value of 0.7 exhibited by the Property Crime category indicates that crime rates in this grouping increased by an average of 0.7 in each census tract. As displayed by the data, this category of crimes displayed an overall increase between the control and variable

temporal periods. The Property Crime category was the only category studied to exhibit any type of increase.

Table 10: Wilcoxon Signed Rank Test of Property Crime Offenses Results

Observations (N)	623
Increase Exhibited	323
Decrease Exhibited	293
No Change	7
Z Score	2.264
Probability	0.024

As displayed in Table 9, 293 (47.03%) Census Tracts experienced a decrease in Property Crime categorized crime rates, 7 (1.12%) experienced no change, and 323 (51.85%) experienced an increase in crime rates. These numbers indicate that slightly over half, 52 percent, of Census Tracts in San Diego County experienced an increase in crime rates for this category. And as with other cohorts the crime rate changes were distributed throughout the county, as opposed to focused in a single area. The variance of the data, represented by standard deviations, is displayed in Figure 12.
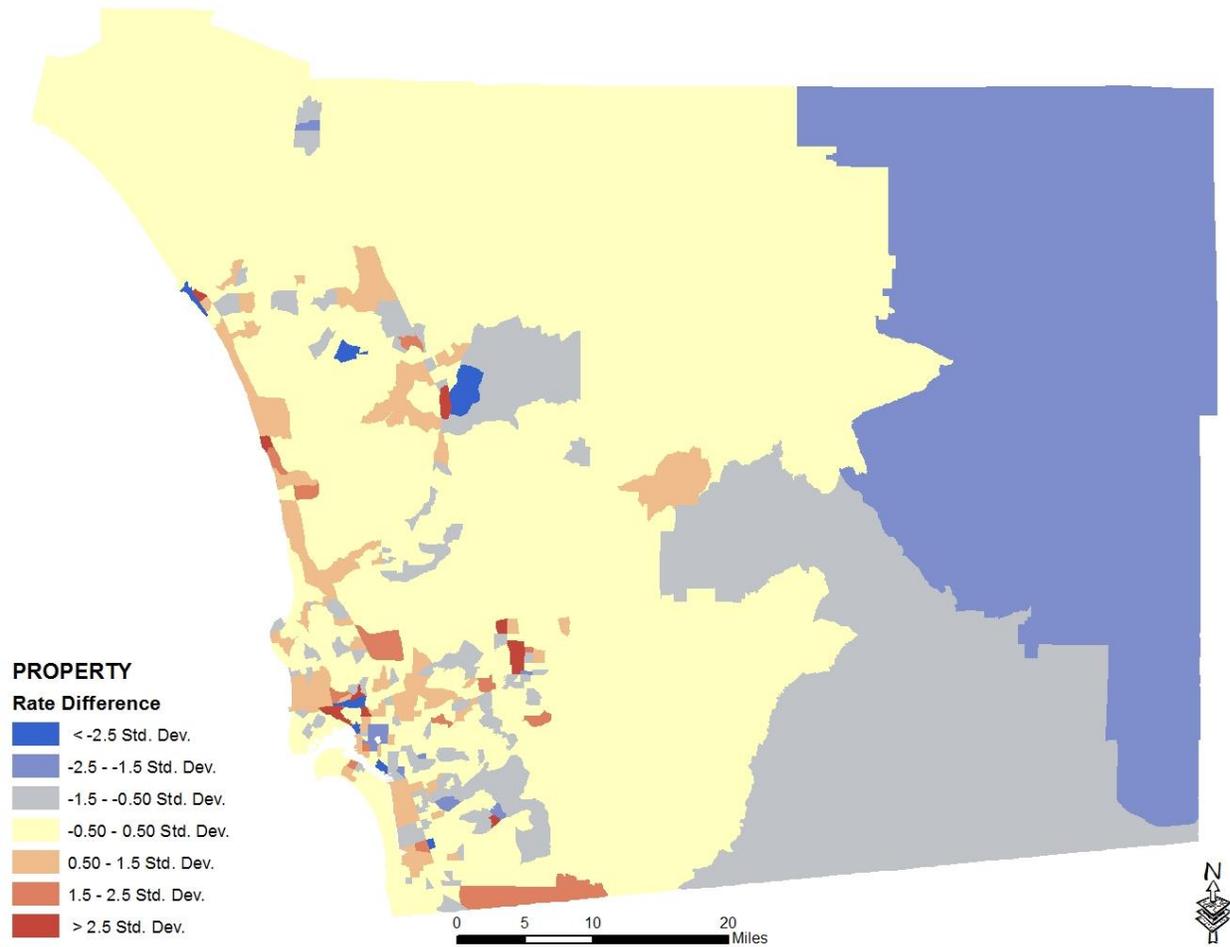
Figure 12: Variance of Property Crime Rate Difference Values

4.1.4. Crimes Against Persons

623 census tracts in San Diego County were included in the analysis of Crimes Against

Persons Offenses. Of the 623 census tracts studied, 318 experienced a decrease in crime rates

during the subsequent period following the implementation of AB 109, 45 experienced no

change, and 260 experienced an increase in crime rates. The results of the Wilcoxon signed-rank

test, displayed in Table 11, indicate a statistically significant median decrease in crime rates of

0.1 events per 1000 people during the temporal period studied, $z=-2.658$, $p = 0.008$. Again, the

small P value indicates the probability of the null hypothesis, AB 109 had no effect on crime

rates, occurring, is less than 1%, indicating statistical significance. Although this test indicated

that a statistically significant drop in crimes against persons occurred during the time studied; the

median decrease in crime rates for the areas studied was -0.1 indicating the change was very

small, 0.1 crimes per 1000 residents.

Table 11: Wilcoxon Signed Rank Test of Crimes Against Persons Offenses Results

Observations (N)	623
Increase Exhibited	260
Decrease Exhibited	318
No Change	45
Z Score	-2.658
Probability	0.008

Although the median decrease of 0.1 crimes per 1000 people is relatively small

compared to the other cohorts studied, it is important to note, as displayed in Table 6, that the

maximum personal crime rate decrease for any Census Tract in the county was 18.47, which is

also relatively small compared to other decreases noted.

As displayed in Table 9, 318 (51.04%) Census Tracts experienced a decrease in personal

crime rates, 45 (7.22%) experienced no change, and 260 (41.73%) experienced an increase in

crime rates. These numbers indicate that slightly over half, 50 percent, of Census Tracts in San

Diego County experienced a decrease in crime rates for this category. Also, as indicated by the

small median decrease in crime rates, these statistics indicate that close to 10% of census tracts

remained stable during the temporal period studied. The variance of the data, represented by

standard deviations, is displayed in Figure 13.

The findings of the analysis are interesting as the statistically significant median value for the census tracts in the county was negative, whereas compared to the aggregate statistics in Section 4.1, counts displayed an increase of 24,549 (1.74%). The negative median finding also contrasts Lofstrom and Raphael's report that indicated "violent crime [rates]" have increased in California, as the crimes against persons cohort is represented mostly by violent crime types. (Lofstrom and Raphael, 2013, pp 2).
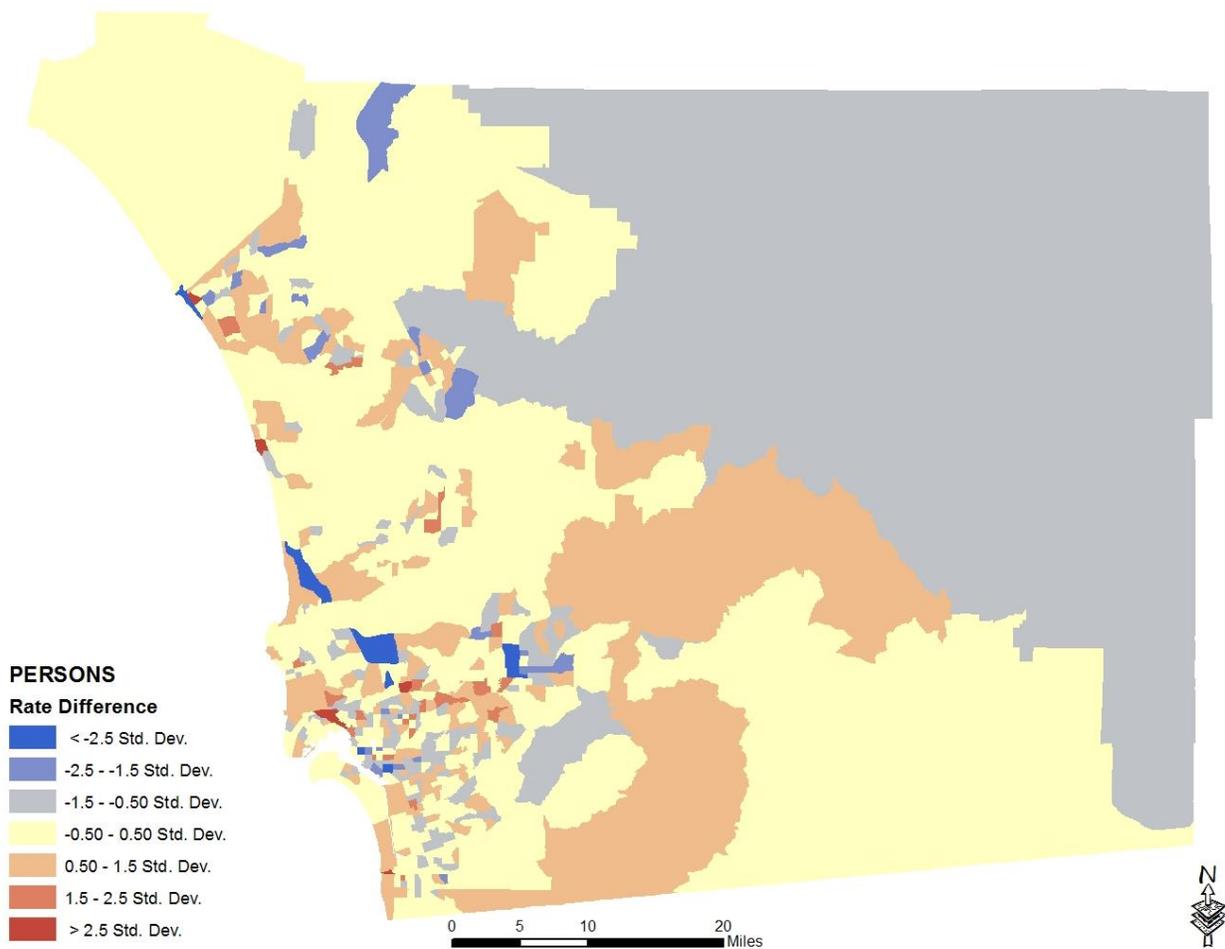
Figure 13: Variance of Persons Crime Rate Difference Values

4.1.5. Crimes Against Society

As stated above with the other cohorts, in total, 623 census tracts in San Diego County were included in the analysis of Crimes Against Society categorized Offenses. Of the 623 census tracts studied, 488 experienced a decrease in crime rates during the subsequent period following the implementation of AB 109, 8 experienced no change, and 127 experienced an increase in crime rates. The results of the Wilcoxon signed-rank test, displayed in Table 12, indicated a statistically significant decrease in crime rates of 3.5 events per 1000 people during the temporal period studied, z=-14.905, p < 0.0005.

**Table 12: Wilcoxon Signed Rank Test of Crimes Against Society Offenses Results**

Observations (N)	623
Increase Exhibited	127
Decrease Exhibited	488
No Change	8
Z Score	-14.905
Probability	< 0.0005

The median value of -3.5 exhibited by the Societal Crime category indicates that crime rates in this grouping decreased by an average of 3.5 events per 1000 people in each census tract. As displayed by the data, this category of crimes displayed an overall decrease between the control and variable temporal periods. The Societal Crime category exhibited the largest median decrease of all crime types studied.

The Societal Crime maximum decrease displayed in Table 6 of -240.34 was the also the largest decrease of crime rates of any of the cohorts studied. This finding reflects the data displayed in Section 4.1.

As displayed in Table 9, 488 (78.33%) Census Tracts experienced a decrease in Societal

Crime categorized crime rates, 8 (1.28%) experienced no change, and 127 (20.38%) experienced

an increase in crime rates. These numbers indicate that a large majority, almost 80 percent, of

Census Tracts in San Diego County experienced a decrease in crime rates for this category, as

reflected by the median decrease in crime rates. The variance of the data, represented by standard

deviations, is displayed in Figure 14.

All tests contained a small P value indicating the probability of the null hypothesis, that

AB 109 had no effect on crime rates, occurring, is less than 1%, indicating statistical

significance.
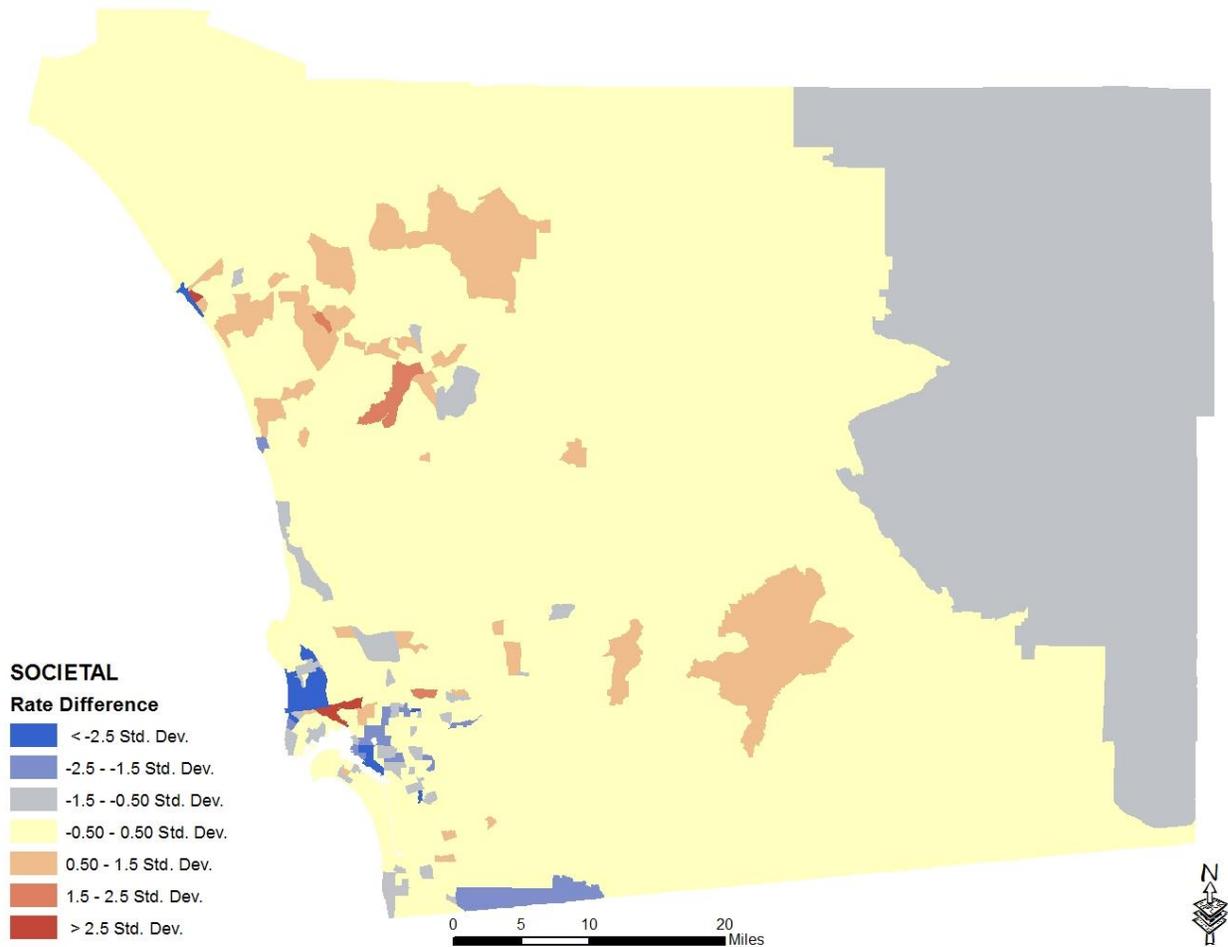
Figure 14: Variance of Societal Crime Rate Difference Values

4.2 Spatial Statistics

Having analyzed the numbers and statistical trend of the data it is clear that property crimes in San Diego County have the increased slightly since the implementation of AB 109. Studies on this subject have also contended that property crime has increased as a result of AB 109; for example Magnus Lofstrum contends there is "robust evidence that realignment is related to increased property crime" (Lofstrom and Raphael, 2013, pp 2). Although Lofstrom's study focused on the State of California as a whole, the data from San Diego County suggest similar results (Lofstrom and Raphael, 2013).

Additionally, although other cohorts did not exhibit an increase in crime rates over the period studied, as with any county, San Diego experienced hot spots of crime where each cohort exhibited a statistically significant increase and cold spots where the cohorts exhibited a statistically significant decrease. Hot spots from each cohort were identified and studied using hot spot and regression analysis, to determine explanatory variables.

4.2.1. Crimes Against Property

Traditional statistics, from this study and others, suggest property crime rates throughout the county have increased slightly immediately following the implementation of Realignment. In an attempt to further study this trend, several spatial factors were analyzed to assess their relationship, if any, to the slight increase in property crime exhibited by the data.

Areas where crime increased, or hot spots, were first identified. As displayed in Figure 15, a hot spot of crime rate increase, identified with a 90% and above confidence level, was located in the Torrey Pines/Del Mar area and extended eastward into the Rancho Bernardo area of San Diego County. Interestingly, no cold spots were identified when analyzing the property crime data aggregated at the census tract level. Within the hot spot, the maximum crime rate

increase was 29.1 as displayed in Table 13. Conversely the minimum crime rate change

exhibited in the hot spot was reported as -47.2. The mean difference was 1.9 over the area of the

hot spot.

Table 13: Range of Property Hot Spot Rate Increase

Maximum	29.1
Minimum	-47.2
Mean	1.9

Figure 15: Property Crime Hot Spots

The *Hot Spot Analysis (Getis Ord Gi*)* tool, identifies relationships between neighboring features, therefore, a range of scores for each polygon is possible, as neighboring polygons may exhibit influence where lower scores are exhibited, hence the -47.2 score.

Once the property crime hot spot was identified, an ordinary least squares model was constructed and tested on a selection of the census tracts contained within the hot spot. The ordinary least squares model or OLS was used to determine the relationship between the variables identified in this study. The dependent variable identified, was the difference in crime rates for the category specified. The explanatory variables identified were Educational Attainment, Employment Status, Marital Status, Poverty Status, Median Household Income, Work Status, Household and Families, and AB 109 Offender locations. Many tests and exploration of the data were completed.

After completion of the model, using *JMP* and *ArcGIS* tools, it was determined that the only variable exhibiting any type of statistical significance was the residence locations of AB 109 offenders with an R^2 of 0.315 and adjusted R^2 of 0.302 as displayed in Table 14. However, upon investigation of the residuals of the model, it was determined that the residuals were autocorrelated, and therefore the model could not be trusted. Many attempts were made to obtain a complete model, however it was determined with any combination or transformation of variables tested in this study, every model constructed was misspecified. As all models were misspecified and only one variable was identified as being statistically significant as part of a misspecified model, it was determined that no significant relationship existed between the hot spot of increase in property crime rates and any of the explanatory variables tested when aggregated at the census tract level. Some other combination of complex variables not listed or

tested as part of this study is responsible for the variance of the hot spot of property crime rate increase when aggregated at the census tract level.

Table 14: Results of Misspecified Property Crime Rate Model

Observations (N)	52
R²	0.315
Adjusted R²	0.302
AIC	377.74
Joint F-Statistic	23.04*
Joint-Wald Statistic	15.40*

* Indicates Statistical Significance

4.2.2. AB 109 Categorized Offenses

AB 109 categorized offenses displayed a significant decrease in median crime rates between the periods studied. However, even though the entire county exhibited an overall decrease, some areas exhibited an increase as identified by hot spot analysis. The hot spot for this crime category was located, and OLS analysis was performed to determine the relationship, if any with the variables studied in this work.

Areas where crime increased, or hot spots, were identified. As displayed in Figure 16, a hot spot of crime rate increase, identified with a 90% and above confidence level, was located in the north western region of San Diego County. A cold spot was also identified in the south western region of the County when aggregated at the census tract level. Within the hot spot, the maximum crime rate increase was 113.0 as displayed in Table 15. Conversely the minimum crime rate change exhibited in the hot spot was -241.9. The mean difference was 1.1 over the

area of the hot spot. The wide range in crime rate change values indicate a large variance in the

clustered hot spot of crime rate increase.

Table 15: Range of AB 109 Rate Increase Hot Spot

Maximum	113.0
Minimum	-241.9
Mean	1.1

As with property crime rates, an OLS analysis of the AB 109 hot spot was completed.
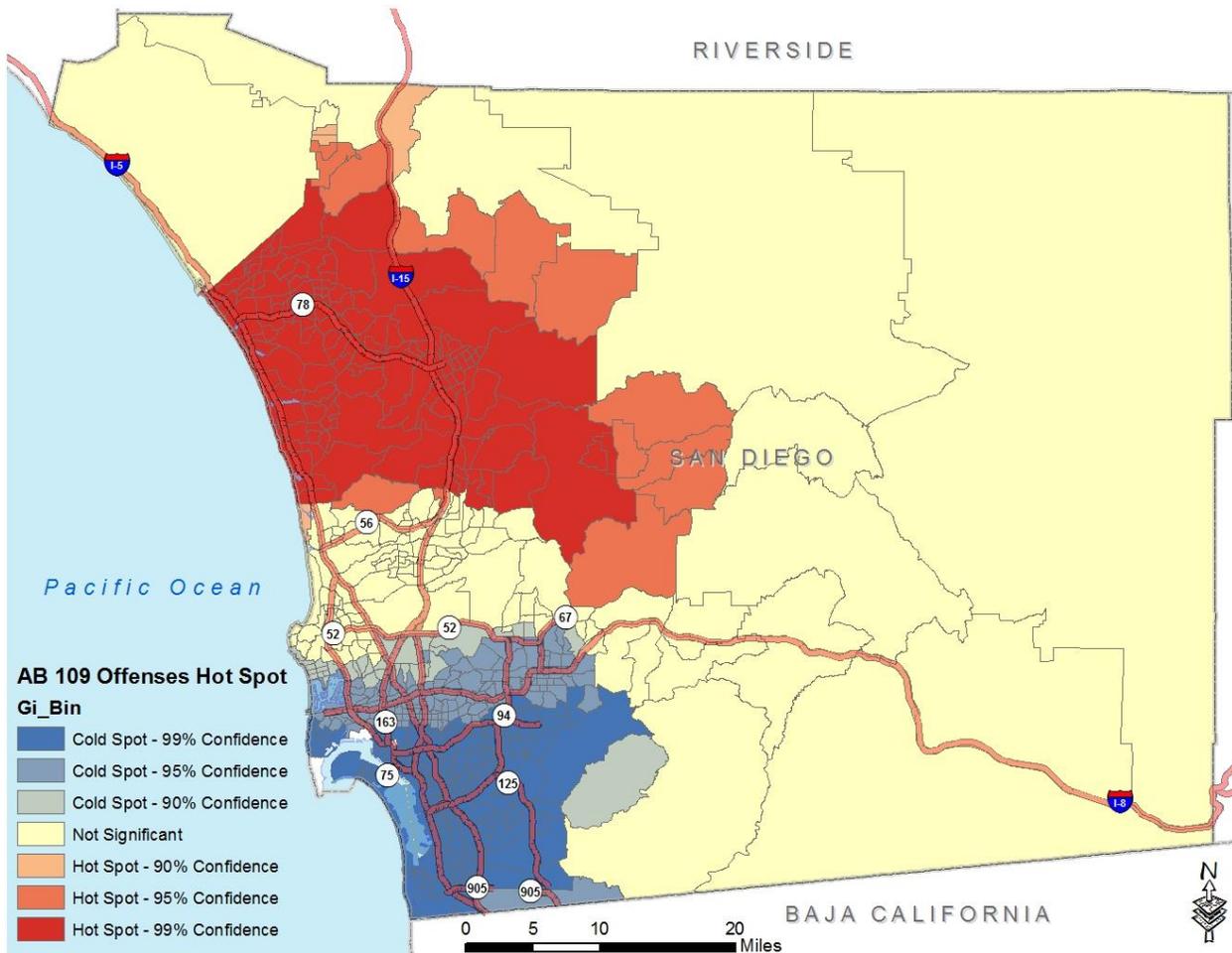
Figure 16: AB 109 Categorized Offenses Crime Rate Change Hot Spot

After completion of the model, using the *JMP* and *ESRI* tools, it was determined that none of the

variables tested exhibited any type of statistically significant influence on the change in crime rates. Many attempts were made to obtain a complete model, however it was determined any combination or transformation of variables tested in this study, produced a misspecified model with no statistically significant variables. As all models were misspecified, it was determined that no significant relationship existed between the hot spot of increase in AB 109 crime rates and any of the explanatory variables tested when aggregated at the census tract level. Some other combination of complex variables not listed or tested as part of this study is responsible for the variance of the hot spot of AB 109 crime rate increase when aggregated at the census tract level.

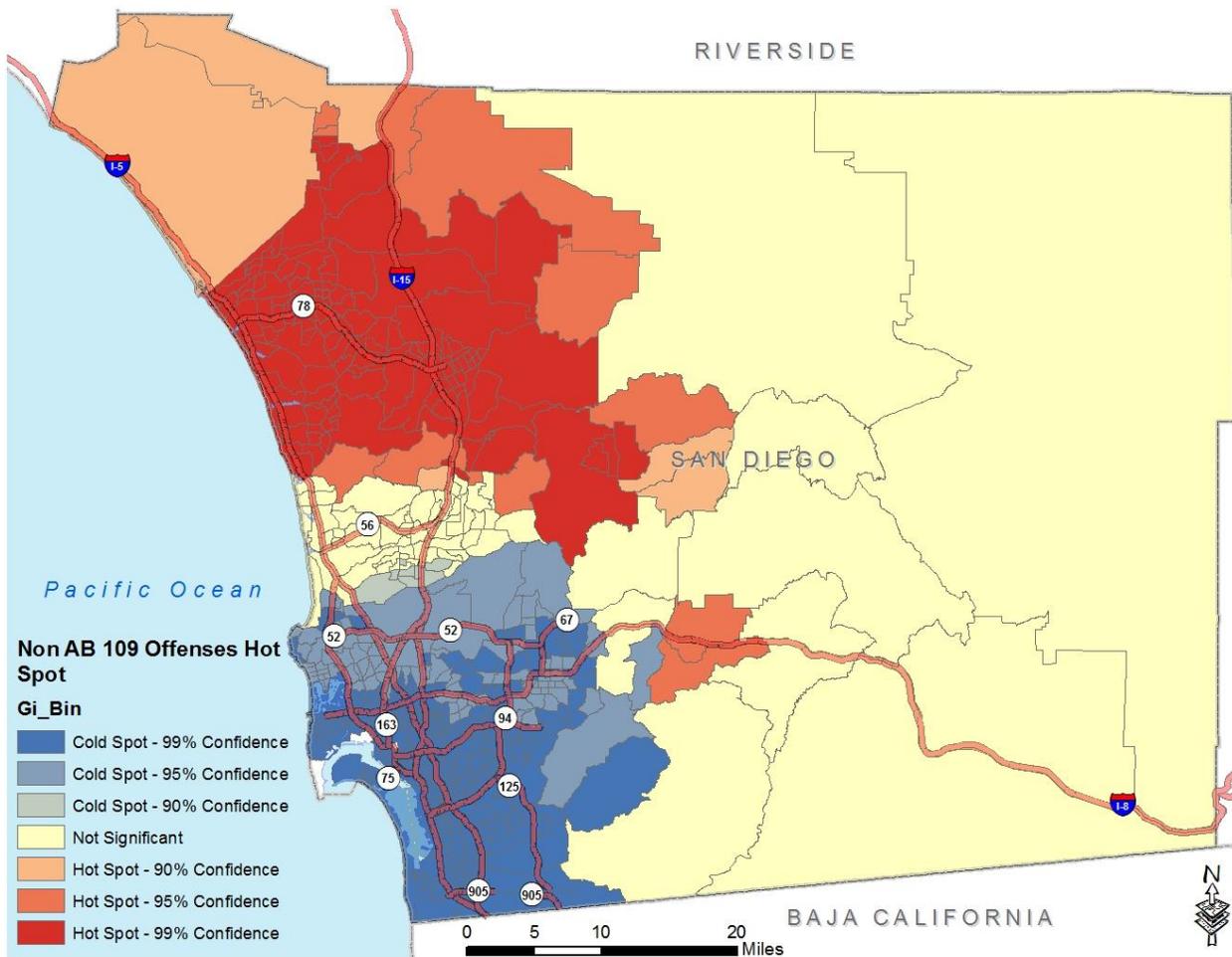### 4.2.3. Non AB 109 Categorized Offenses

Non AB 109 categorized offenses also displayed a significant decrease in median crime rates between the periods studied. As with AB 109 offenses, the data was studied to determine if there was a significant hot spot where crime rates increased or decreased. A hot spot was identified for this crime category, and OLS analysis was performed to determine the relationship, if any with the variables studied.

Areas where crime increased, or hot spots, were identified. As displayed in Figure 17, a hot spot of crime rate increase, identified with a 90% and above confidence level, was located in the north western region of San Diego County. A cold spot was also identified in the south western region of the County when aggregated at the census tract level. Within the hot spot, the maximum crime rate increase was 14.9 as displayed in Table 16. Conversely the minimum crime rate change exhibited in the hot spot was -43.4. The mean difference was -1.4 over the area of the hot spot.

Table 16: Range of Non AB 109 Rate Increase Hot Spot

Maximum	14.9
Minimum	-43.4
Mean	-1.4

As with property crime rates and AB 109 crime rates, an OLS analysis of the Non AB 109 hot spot was completed. After completion of the model, using the *JMP* and *ESRI* tools, it was determined that the only variable exhibiting any type of statistical significance was Poverty Status with an R^2 of 0.041 and adjusted R^2 of 0.035. However, upon investigation of the model parameters, it was determined that the "Jarque-Bera Statistic" was statistically significant, and

Figure 17: Non AB 109 Categorized Offenses Crime Rate Change Hot Spot

therefore the model could not be trusted as a statistically significant "Jarque-Bera" values indicates non-normal residual distribution and possible model misspecification (ESRI, 2013). Many attempts were made to obtain a complete model, however it was determined with any combination or transformation of variables tested in this study, every model constructed was misspecified. As all models were misspecified and only one variable was identified as being statistically significant as part of a misspecified model, it was determined that no significant relationship existed between the hot spot of increase in Non AB 109 crime rates and any of the explanatory variables tested when aggregated at the census tract level. Even though the poverty status of the population was identified as possibly being statistically significant, the R^2 value was less than 0.05, meaning that only 5% of the variance was potentially explained with this variable. Therefore it was determined that some other combination of complex variables not listed or tested as part of this study is responsible for the variance of the hot spot of Non AB 109 crime rate increase when aggregated at the census tract level.

4.2.4. Crimes Against Society

Societal Crime rates displayed the most significant decrease in median crime rates between the periods studied. As with AB 109 offenses, the data was studied to determine if a significant hot spot of crime rate increase or decrease between the periods studied was exhibited. After investigation, a hot spot was identified for this crime category, and OLS analysis was performed to determine the relationship, if any with the variables studied.

Areas where crime increased, or hot spots, were identified. As displayed in Figure 18, a hot spot of crime rate increase, identified with a 90% and above confidence level, was located in the north western region of San Diego County. A cold spot was also identified in the south western region of the County when aggregated at the census tract level. Within the hot spot, the

maximum crime rate increase was 54.7 as displayed in Table 17. Conversely the minimum crime rate change exhibited in the hot spot was -206.4. The mean difference was -1.5 over the area of the hot spot. The wide range in crime rate change values indicate a large variance in the clustered hot spot of crime rate increase.

Table 17: Range of Societal Crime Rate Increase Hot Spot

Maximum	54.7
Minimum	-206.4
Mean	-1.5
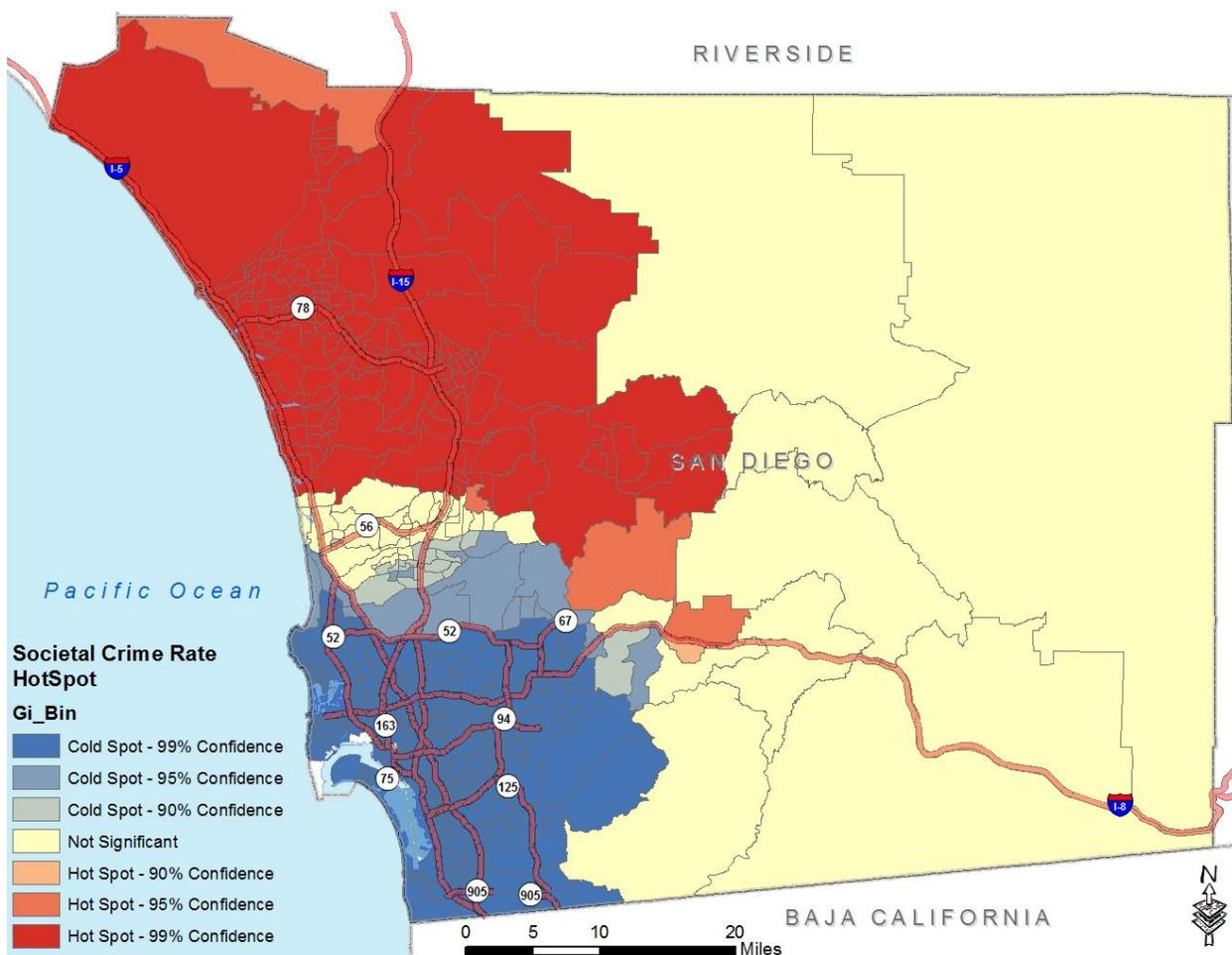
Figure 18: Societal Crime Rate Change Hot Spot

As with property crime rates, an OLS analysis of the societal crime rate hot spot was completed. After completion of the model, using the *JMP* and *ESRI* tools, it was determined that none of the variables tested exhibited any type of statistically significant influence on the change in crime rates. Many attempts were made to obtain a complete model, however it was determined any combination or transformation of variables tested in this study, produced a misspecified model with no statistically significant variables. As all models were misspecified, it was determined that no significant relationship existed between the hot spot of increase in societal crime rates and any of the explanatory variables tested when aggregated at the census tract level. Some other combination of complex variables not listed or tested as part of this study is responsible for the variance of the hot spot of societal crime rate increase when aggregated at the census tract level.

4.2.5. Crimes Against Persons

Unlike the other categorized offense types, crimes against persons in San Diego County, did not exhibit a significant increase or decrease in crime rates. The median change in crime rates between the periods studied was very small; almost zero. Hot spot analysis was used to determine if any areas of significant increase in persons crime rates occurred. An OLS analysis was performed on the hot spot and statistically significant variables were identified.

Table 18: Range of Persons Crime Rate Increase Hot Spot

Maximum	2.4
Minimum	-2.5
Mean	0.0

Areas where crime increased, or hot spots, were identified. As displayed in Figure 19, a hot spot of crime rate increase, identified with a 90% and above confidence level, was located in

the Rancho Bernardo area of San Diego County. A cold spot was also identified in the south eastern region of the County when aggregated at the census tract level. Within the hot spot, the maximum crime rate increase was 2.4 as displayed in Table 18. Conversely the minimum crime rate change exhibited in the hot spot was -2.5. The mean difference was 0.0 over the area of the hot spot.

Figure 19: Persons Crime Rate Change Hot Spot

Table 19: Persons Crime Rate Change Hot Spot OLS Model Results

Observations (N)	10
R²	0.961
Adjusted R²	0.913
AIC	70.54
Joint F-Statistic	23.04* (p = 0.006282)
Joint-Wald Statistic	15.40* (p = 0.000000)

* Indicates Statistical Significance

As a hot spot of crime rate increase was identified, an OLS analysis was performed. The dependent variable used was, again, the difference in property crime rates between the two temporal periods studied. All explanatory variables identified for the study were tested and a properly specified model was identified.

When analyzed using OLS regression analysis, the hot spot exhibited an R² of 0.961 and an adjusted R² of 0.913, meaning that it describes 91% of the variation. The variables found to influence the change in crimes against persons rates were as follows: Educational Attainment, Marital Status, Level of single parent households and the distance from the freeway. Appendix A further explains the actual variables used to represent the categories listed above. In the case of this model: Percent Bachelors or Higher Difference (2013-2010) and Percent High School or Higher represent Educational Attainment, Percent Divorced Difference (2013-2010) represents Marital Status and the Count of Single Parent Households represents the Level of single parent households. These variables exhibited a statistically significant Joint F and Joint Wald Statistic above a 95% confidence with a p-value less than 0.05; 0.00628 and 0.00000 as displayed in Table 19.

Table 20: Moran's I Result of Crimes Against Persons OLS Residuals

Moran's Index:	-0.228088
Expected Index:	-0.111111
Variance:	0.017442
z-score:	-0.885728
p-value:	0.375764
Moran's Index:	-0.228088

To ensure that the Ordinary Least Squares model was not autocorrelated, the *ArcGIS Spatial Autocorrelation (Moran's I)* tool was used to analyze the residuals. Moran's I will determine if there is clustering within the residuals and indicate if the model is misspecified. The residuals of the model were identified as random with no clustering. The residuals of the crimes against persons model are displayed in Figure 20 and the results from the Moran's I tool used to test the clustering of residuals are contained in Table 20.
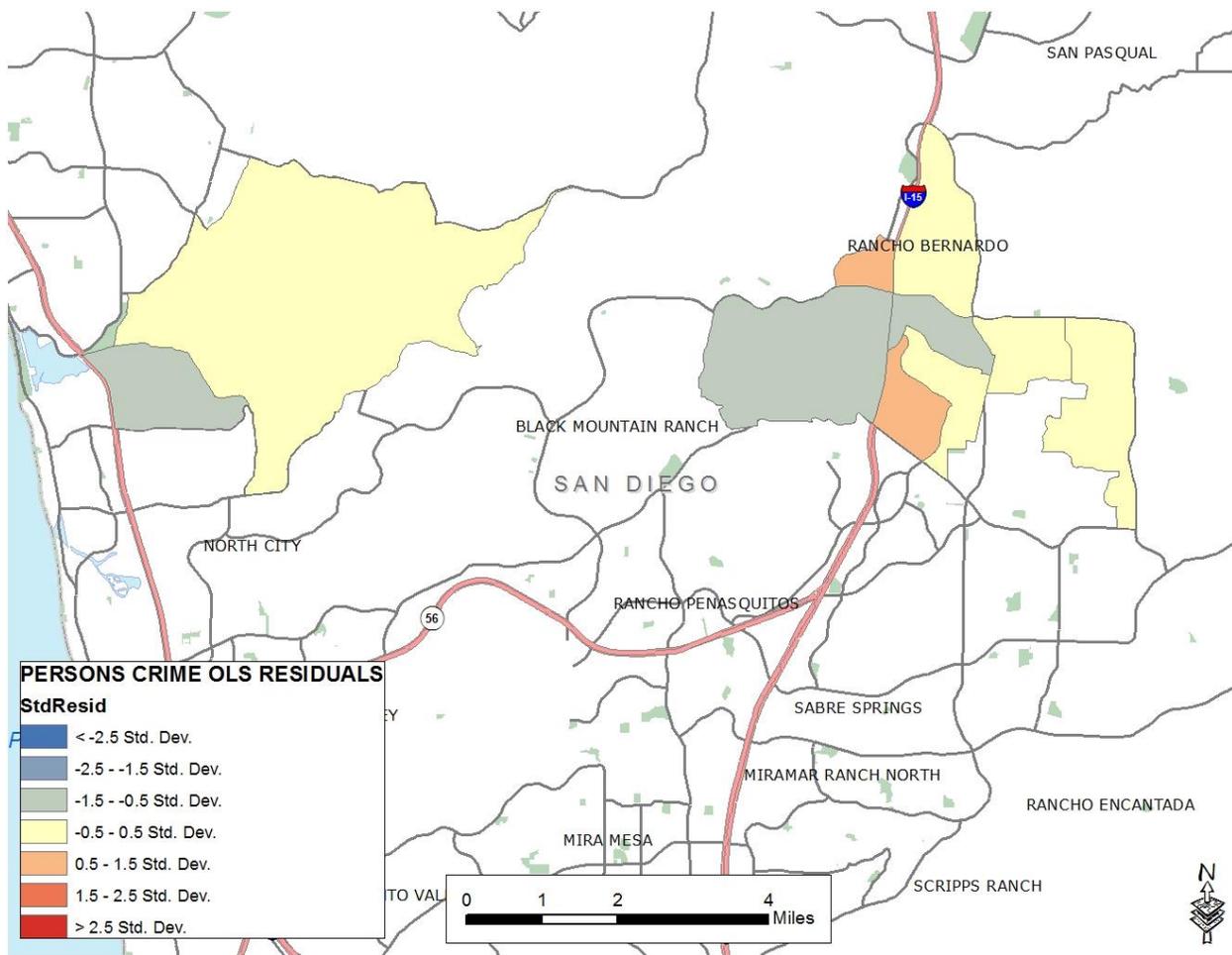
Figure 20: Standard Residuals of the OLS Crimes Against Persons Model

Chapter 5 Discussion and Conclusions

With all of the statistics calculated and completed, it is important to discuss the reasons and assumptions of the research and draw any conclusions from the results. The primary purpose of this study was to determine the spatial effect of AB 109 on crime rates in San Diego County. A literature review was completed studying the spatial characteristics of criminal offenders and assumptions were made. It is a hope of this work that identifying spatial relationships behind changes in crime rates will help determine the reasons why crime rates are changing and hopefully make solutions more apparent.

The general purpose of this work, as stated above, is to determine the spatial effect of AB 109, if any, on crime rates in San Diego County. A primary assumption in this work is that offenders will likely commit offenses near their place of residence. With this assumption, a primary hypothesis and null hypothesis were formed. The hypothesis can be stated as "Do areas where larger numbers of AB 109 offenders reside exhibit an increase in crime rates?" Therefore the null hypothesis can be stated as "Areas in which larger numbers of AB 109 offenders reside do not exhibit an increase in crime rates."

To study this hypothesis, a traditional statistical analysis and a spatial OLS regression analysis were completed on five categories of crimes. To reject the null hypothesis and indicate that AB 109 is having an effect on crime rates in San Diego County, this study would expect to see clustered areas exhibiting an increase in crime rates, correlated to populations of AB 109 offenders. Each category was studied individually using a multitude of variables identified as historically having an influence on crime rates by the FBI as well as residence locations of AB 109 offenders to determine if locations of AB 109 offender or any other social/physical characteristic had an influence on crime rates (Federal Bureau of Investigation, 2006).

5.1 Conclusions

The results of the traditional statistical analysis indicated that of the five crime categories studied, four exhibited an overall median decrease in crime rates across the county and one, property crime, exhibited a slight increase. This indicates that overall, crime rates have decreased in San Diego County following the implementation of AB 109. Societal crime exhibited the largest decrease in crime rates when aggregated at the census tract level, a median decrease of -3.5 crimes per 1000 persons.

A closer look into the statistics reveals some interesting trends have occurred since the implementation of AB 109. For example, while societal crime exhibited a large decrease in crime rates and overall counts, property crime exhibited a slight increase. A closer investigation into the property crime cohort indicates that burglary counts, a type of crime falling under the property crime cohort, have increased following the implementation of AB 109, to their highest levels over the temporal period studied. Thefts and larcenies also exhibited a similar increase, the cohort exhibited the highest count during the period following the implementation of Realignment.

The temporal statistics indicate that realignment may have had an effect of property crime in San Diego County. The conclusion that property crime rates have increased as a result of realignment has been drawn by other studies using temporal statistics (Beard et al, 2013; Lofstrom and Raphael, 2013). This study investigated this claim with temporal statistics and found that the data for San Diego County supported this conclusion.

This study further investigated this increase through the use of spatial statistics. An OLS regression model was constructed to establish the variables behind the increase in a hot spot if census tracts identified in the county. After multiple attempts were made to identify a model that

explained the variance behind the hot spot of crime rate increase, it was determined that all models constructed were misspcified, and therefore could not be trusted. The results of the OLS models suggested that some other combination of complex variables not listed or tested as part of this study is responsible for the variance of the hot spot of property crime rate increase when aggregated at the census tract level.

Therefore the null hypothesis, "Areas in which larger numbers of AB 109 offenders reside do not exhibit an increase in crime rates" could not be rejected for the property crime cohort. Therefore the results of this study suggest increased populations of AB 109 offenders do not correlate with an increase of property crimes rates when data are aggregated at the census tract level.

Apart from property crime, no other crime category cohorts exhibited any type of significant relationship between their respective crime rate increase hot spots and AB 109 offenders. Therefore the null hypothesis, "Areas in which larger numbers of AB 109 offenders reside do not exhibit an increase in crime rates" could not be rejected.

Additionally a secondary hypothesis of the study, "do other social and physical variables explain the hot spot of increase in crime rates?" was tested by using other social and physical variables as part of the OLS models. The secondary null hypothesis could not be rejected for all cohorts except crimes against persons.

AB 109 and Non-AB 109 categorized offenses as well as crimes against society exhibited no significant correlation or relationship to any variable tested and no variables contained a strong p-value, when compared against the identified hot spots of crime rate increase. Therefore the null hypothesis associated with the secondary hypothesis, "other social and physical variables do not explain the hot spot of increase in crime rates" could not be rejected.

However one cohort's hot spot, crimes against persons, displayed a very high R² value of 0.961 and adjusted R² value of 0.913, displayed in Table 19, explaining 91% of the variance for the hot spot with the other social and physical variables. The variables found to explain this cohort's hot spot were: Educational Attainment, Marital Status, Level of single parent households and the distance from the freeway. Therefore it can be stated that the implementation of AB 109 or realignment did not have any ascertainable effect on crimes against persons rates. Traditional statistics methods indicated that the median decrease of crime rates in census tracts across the county was almost zero and the spatial statistics studying the hot spot of crime rate increase clearly illustrate a different combination of variables apart from AB 109 offenders is correlated with the hot spot of crime rate increase.

5.2 Sources of Error

After the analysis of the data was complete, possible sources of error were identified; a brief discussion of the sources of error follow.

AB 109 and Non AB 109 categories were identified and analyzed as part of the study. The list of statutes punishable under the AB 109 provision are not always straight forward; for example, certain types of burglaries are now sentenced under AB 109 guidelines, while other types of burglaries are not (Couzens, 2013; Harris and Donaldson, 2013). DUIs represent another crime type where certain types of DUIs fall under AB 109 sentencing guidelines and some others do not (Byers, 2011). To account for this the data was evaluated and crimes were divided into each category based on estimation, as the only data to determine whether or not a crime could be sentenced under the AB 109 provision was a brief description field in the data. For the purposes of this analysis, burglaries fell under the AB 109 category and DUIs fell under the Non AB 109 category however it was noted that some misclassification could have occurred.

In conjunction with the complication of querying the data for complex categories of crimes, it also noted that the queries used to separate the AB 109 and Non AB 109 categories were also complex. The queries were constructed as to separate certain types of crime and to select other types in order to make the best effort to properly select the crimes for each category. Due to the complexity of the queries and the crime category divisions, it is noted that a small number of reported crimes were selected for both categories. Additionally it is noted that some reported crimes may not been selected due to the complexity of the query. It is estimated that this error source affected 415 (0.076%) out of 548,306 records.

Additionally when aggregating incident counts at the census tract level, a spatial join technique was used, creating double counts in some cases. When a spatial join is used, the tool counts the number of features that intersect the feature being joined. A point may be counted twice, once in each polygon, if the point or other feature falls on the boundary of two intersecting polygons. There is no good way to determine where this might occur and no easy workaround, therefore it is included as a source of error in the analysis.

5.3 Future Work

This work has indicated that many crime categories have exhibited a decrease in crime rates following the implementation of AB 109, however property crime has increased slightly. Other works, studying the state as a whole and using temporal statistics, have also concluded that realignment is correlated with the increase in property crime rates across the state (Beard et al, 2013; Lofstrom and Raphael, 2013). This work would suggest that as a slight increase was exhibited in San Diego County, other counties should also be studied to determine similarities or differences between the results.

Additionally, this work analyzed crime rates and trends coinciding with the implementation of AB 109 through 2013. Future work could study the property crime trend for future years.

Lastly, this work studied a statue that represents a major restructuring in the way that offenders are sentenced. This work investigated the effect of the statute on crime rates in San Diego County. In the time that this work was completed, another statue, California Proposition 47, was passed, which would change how offenders of similar crime types are sentenced. Future work should be done to assess the impact of proposition 47 as it also represents a major shift in the way offenders are processed.

REFERENCES

"San Diego: Geography and Climate." 2006. In *Cities of the United States*. 5th ed. ed. Vol. 2, 193. Detroit: Gale.

Beard, Jeffrey A., Diana Toche, Bryan Beyer, Wayne Babby, Denise Allen, Kevin Grassel, and Dionne Maxwell. 2013. *Realignment Report: An Examination of Offenders Released from State Prison in the First Year of Public Safety Realignment*. Sacramento: California Department of Corrections And Rehabilitation. http://www.cdcr.ca.gov/Adult_Research_Branch/Research_Documents/Realignment_1_Year_Report_12-23-13.pdf.

Brandmüller, Teodóra and Åsa Önnerfors, eds. 2011. *Eurostat Regional Yearbook 2011*. 1st ed. Luxembourg: Publications Office of the European Union.

Brantingham, Paul J. and Patricia L. Brantingham. 1981. "Introduction: The Dimensions of Crime." In *Environmental Criminology*, edited by Paul J. Brantingham and Patricia L. Brantingham. 1st ed., 7. Beverly Hills: Sage.

Byers, Garrick. 2011. *Realignment*. 1st ed. Continuing Education of the Bar: California. ceb.com/lawalerts/realignment.doc.

Cain, Sandi. 2005. "San Diego Coast, Downtown are Visitor Magnets: Diverse Geography and Activities Keep Tourists Coming Back." *San Diego Business Journal* 26 (27): A-19. http://bi.galegroup.com.libproxy2.usc.edu/essentials/article/GALE;A135021433?u=usocal_main;.

Californians for Safety and Justice. "About Public Safety Realignment." Californians for Safety and Justice, last modified 2013, accessed 02/07, 2015, http://www.safeandjust.org/CalRealignment/About-Realignment.

Charlton, Martin. 2008. "Modifiable Areal Unit Problem (MAUP)." In *Encyclopedia of Geographic Information Science*, edited by Karen K. Kemp. 0th ed., 289-291: SAGE Publications, Inc. doi:http://dx.doi.org/10.4135/9781412953962".

County of Los Angeles Probation Department. "Ab 109." County of Los Angeles, accessed September/28, 2015, http://probation.lacounty.gov/wps/portal/probation/!ut/p/b0/04_Sj9CPykssy0xPLMnMz0vMAfGjzOLdDAwM3P2dgo3cvX2NDBwNHD0d_T3DDE3cTfULsh0VAXzjOO8!/.

Couzens, J. Richard. 2013. "Realignment and Evidence-Based Practice: A New Era in Sentencing California Felonies." *Federal Sentencing Reporter* 25 (4, Realigning California

Corrections): 217-219.
http://www.jstor.org.libproxy.usc.edu/stable/10.1525/fsr.2013.25.4.217.

ESRI. "Interpreting OLS Results." ESRI, last modified 4/18/2013, accessed 12/7, 2015,
http://resources.arcgis.com/en/help/main/10.1%20/index.html#/Interpreting_OLS_results/00
5p00000030000000/.

Federal Bureau of Investigation. "Variables Affecting Crime." U.S. Department of Justice, last
modified September 2006, accessed 10/25, 2015,
https://www2.fbi.gov/ucr/05cius/about/variables_affecting_crime.html.

Godwin, Maurice and David Canter. 1997. "Encounter and Death the Spatial Behavior of US
Serial Killers." *Policing* 20 (1): 24.
http://search.proquest.com.libproxy.usc.edu/docview/211290067?accountid=14749.

Harries, Keith. 2006. "Property Crimes and Violence in the United States: Analysis of the
Influence of Population Density." *International Journal of Criminal Justice Sciences* 1 (2).
http://www.sascv.org/ijcjs/harries.html.

Harris, Heather and Donaldson, Michael. "AB 109: Eligible 1170(h) Felonies List." County
Santa Clara Public Defender Office, last modified 3/13/2013, accessed September/28, 2015,
https://www.sccgov.org/sites/pdo/Pages/AB-109--Eligible-1170(h)-Felonies-List.aspx.

Heyman, Steven J. 1991. "The First Duty of Government: Protection, Liberty and the Fourteenth
Amendment." *Duke Law Journal* 41 (3): 507-571.

International Association of Crime Analysts. 2013. *Identifying High Crime Areas (White Paper
2013-02)*. Overland Park, KS: International Association of Crime Analysts.

Laerd Statistics. "Paired-Samples T-Test in SPSS Statistics." Laerd Statistics. Lund Research
Ltd, accessed 11/23, 2015, https://statistics.laerd.com/premium/pstt/paired-samples-t-test-in-
spss-8.php.

Langan, Patrick and David Levin. 2002. *Recidivism of Prisoners Released in 1994: United
States*. Washington, DC: U.S. Department of Justice: Bureau of Justice Statistics.
http://www.bjs.gov/content/pub/pdf/rpr94.pdf.

Law Enforcement Support Section (LESS) and Crime Statistics Management Unit (CSMU).
2013. *Criminal Justice Information Services (CJIS) Division Uniform Crime Reporting
(UCR) Program National Incident-Based Reporting System (NIBRS) User Manual*: U. S.
Department of Justice.

Lawton, Brian A., Ralph B. Taylor, and Anthony J. Luongo. 2005. "Police Officers on Drug
Corners in Philadelphia, Drug Crime, and Violent Crime: Intended, Diffusion, and
Displacement Impacts." *Justice Quarterly : JQ* 22 (4): 427-451.
http://search.proquest.com.libproxy.usc.edu/docview/228177699?accountid=14749.

Lofstrom, Magnus and Steven Raphael. 2013. *Public Safety Realignment and Crime Rates in California*. San Francisco: Public Policy Institute of California. www.ppic.org/main/publication.asp?i=1075.

Munyo, Ignacio and Martin A. Rossi. 2015. "First-Day Criminal Recidivism." *Journal of Public Economics* 124: 81-90. doi:10.1016/j.jpubeco.2014.12.002.

Murack, Jennie. "Regression Analysis using ArcMap" MIT Libraries, accessed 9/20, 2015, https://libraries.mit.edu/files/gis/regression.pdf.

New Jersey State Police."Calculations of Rates and Trends." New Jersey State Police, accessed 11/23, 2015, http://www.njsp.org/info/ucr2000/pdf/calc_ucr2000.pdf.

Openshaw, Stan. 1983. *The Modifiable Areal Unit Problem. Concepts and Techniques in Modern Geography 38*. Norwich, England: Geo Books.

O'Sullivan, David, 1966 and D. (David John) Unwin. 2010. *Geographic Information Analysis*. 2nd ed. Hoboken, N.J: John Wiley & Sons.

Rhodes, William M. and Catherine Conly. 1981. "Crime and Mobility: An Empirical Study." In *Environmental Criminology*, edited by Paul J. Brantingham and Patricia L. Brantingham. 1st ed., 167. Beverly Hills: Sage.

Rossmo, D. Kim. 1997. "Geographic Profiling." In *Offender Profiling: Theory, Research and Practice*, edited by Janet L. Jackson and Debra A. Bekerian, 159.

U.S. Census Bureau. 2002. *California: 2000: Census 2000 Profile*: U.S. Department of Commerce. http://www.census.gov.libproxy2.usc.edu/prod/2002pubs/c2kprof00-ca.pdf.

———. "State & County QuickFacts: San Diego County, California." U.S. Department of Commerce, last modified 04 Dec 2014, accessed 02/07, 2015, http://quickfacts.census.gov/qfd/states/06/06073.html.

———. "State & County QuickFacts: California." U.S. Department of Commerce, last modified 05 Feb 2015, accessed 02/07, 2015, http://quickfacts.census.gov/qfd/states/06000.html.

Weisberg, Robert and Lisa T. Quan. 2014. *Assessing Judicial Sentencing Preferences After Public Safety Realignment: A Survey of California Judges*. Stanford: Stanford Criminal Justice Center. https://www.law.stanford.edu/publications/assessing-judicial-sentencing-preferences-after-public-safety-realignment-a-survey-of-california-judges.

Wilkinson, William Richard, John C. 1929- (John Chynoweth) Burnham, and Joseph F. Spillane. 2005. *Prison Work: A Tale of Thirty Years in the California Department of Corrections*. Columbus: Ohio State University.

Zimring, Franklin E. and Gordon Hawkins. 1994. "The Growth of Imprisonment in California."
    The British Journal of Criminology 34 (SPEISS): 83-96.
    http://www.jstor.org.libproxy2.usc.edu/stable/23638189.

Appendix A: Social and Physical OLS Variables

FBI Variable Category (Census Table)	Social or Physical Variable Used
1. Economic conditions, including median income, poverty level, and job availability (Poverty Status in the Past 12 Months, Median Household Income in the Past 12 Months (In 2010 Inflation-Adjusted Dollars, Employment Status, Work Status in the Past 12 Months)	• Unemployment Rate – 2010 Census • Mean Usual Hours Worked - 2010 Census • Mean Usual Hours Worked Difference (2013-2010) • Mean Usual Hours Worked - 2013 Census ACS counts • Percent Below Poverty – 2010 Census • Percent Below Poverty 2013 Census ACS Counts • Percent Below Poverty Difference (2013-2010) • Median Household Income – 2010 Census • Median Household Income – 2013 Census ACS counts
2. Family conditions with respect to divorce and family cohesiveness (Marital Status, Household and Families)	• Percent Divorced – 2010 Census • Percent Below Poverty – 2013 Census ACS counts • Percent Divorced Difference (2013-2010) • Count of Single Parent Households – 2010 Census
3. Variations in composition of the population, particularly youth concentration (Median Age, Total Population in Housing Units by Tenure)	• Median Age – 2013 Census ACS Counts • Count of Renters – 2013 Census ACS Counts
4. Cultural factors and educational, recreational, and religious characteristics (Educational Attainment)	• Percent Bachelors or Higher 2010 Census • Percent Bachelors or Higher 2013 Census ACS • Percent Bachelors or Higher Difference (2013-2010) • Percent High School or Higher – 2010 Census
5. Stability of the population with respect to residents' mobility, commuting patterns, and transient factors	• Distance from Freeway – Distance calculated from geographic features.

*This list represents all potential variables tested as part of the OLS analysis. Not all variables were used directly; for example a difference value may have been used in place of the 2013 or 2010 Census values.

Source: Federal Bureau of Investigation (2006); Census Bureau (2010 and 2013)