Policing in Socially Disorganized Communities: The Implementation of Community Policing, Crime Analysis, and Policing Technologies

by

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Abstract

The last century has seen a revolution of policing practices across the United States, especially regarding community policing practices, crime analysis, and the utilization of modern technologies. These practices have been implemented across the country in order to improve relationships between the community and their police departments, provide police supervisors with targeted approaches to crime reduction, as well as modernize policing tactics. Each of these aforementioned practices has been proven to have a positive aspect for police departments; however, there has been a lack of research conducted attempting to tie these practices to the theoretical framework of Social Disorganization Theory.

This study uses UCR, LEMAS, and Census data in order to evaluate whether or not there are any relationships between social disorganization levels within a community and its police department's use of community policing practices, crime analysis, and modern technologies. Backwards Stepwise Regression techniques were utilized for the main statistical analysis. Findings indicate that social disorganization levels play a small role in the predictive nature of a department's use of modern technology, and this finding only indicates a weak relationship. Overall, the findings of this study indicate that police departments fail to implement these policing practices in areas that are socially disorganized; however, tailoring these practices towards these areas of high social disorganization will exacerbate their effects in improving relationships and combatting crime rates.

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I miss you more and more every day.

This is for you.

Chapter 1: Introduction

Shaw and McKay introduced Social Disorganization Theory as a result of their research conducted on juvenile delinquency in Chicago in 1942. Succinctly put, Shaw and McKay claimed that crime is prevalent in urban areas where citizens experience low levels of socioeconomic status, high levels of ethnic/racial heterogeneity, and high levels of residential instability. Modern criminological research has supported these claims in 21st century American cities, claiming that it may be the places, not the people, that cause criminal activity to come to fruition (Hays, 2011).

Research conducted by scholars also provides empirical evidence supporting the assumption that ever since the standard model of policing was found to lack the crime reduction capabilities it was supposed to have, police departments have attempted to implement other policing strategies to combat crime (Weisburd & Majmundar, 2018). Examples of these modern forms of policing include community policing, hot spots policing, problem-oriented policing, broken windows policing, intelligence-led policing, and stratified policing.

Evidence supports the claim that community policing facilitates more optimistic relationships between police officers and the community. Community policing efforts have an indirect, positive effect on the reduction of crime, as well as help to improve the legitimacy of the police department in the eyes of the community.

Furthermore, crime analysis has been supported as a strategy to help identify crime patterns and support various policing practices as a result of identifying areas of high crime as well as crime patterns (Santos, 2014). Crime analysts do this through the proper collection, collation, analysis, and dissemination of crime analysis products (O’Shea & Nicholls, 2003).

Overall, it has been supported that the application of proper crime analysis techniques has been found to be a vital aspect of modern policing philosophies that reduce crime (Santos, 2014).

Through the utilization of proactive policing approaches, police departments have adopted new policing technologies such as gunshot detection systems, license plate readers, the enhancement of video surveillance techniques, and the utilization of technology for social media outlets (United States Bureau of Justice Statistics, 2012). All of these technologies have been supported by empirical research to assist departments in crime reduction efforts (Ariel, 2017; Beshears, 2017; Choi, Librett, & Collins, 2014; National Institute of Justice, 1998; Piza, Caplan, Kennedy, & Gilchrist, 2014; Shafique, Zahra, Farid, & Sharif, 2017; Shah & Braithwaite, 2013; Weisburd et al., 2015; Willis, Koper, & Lum, 2018).

This study will attempt to analyze how police departments employ community policing, crime analysis, and modern technologies and determine whether their implementation varies by their communities' levels of social disorganization because of the lack of research in this area. This research is important to conduct in order to develop a deeper understanding of policing practices within a Social Disorganization Theory mindset.

Seeing as crime rates are higher in areas with high levels of social disorganization (Reisig & Parks, 2004; Sampson & Groves, 1989), and practices such as community policing, crime analysis, and modern technology all assist police departments in crime reduction efforts, it would be expected to address crime in these areas, and police would focus these approaches in areas of high levels of social disorganization.

The goal of the research is to help develop a better understanding of policing and how it is implemented in terms of community policing, crime analysis, and modern technology for communities with different levels of social disorganization and crime. In order to address these topics, multiple regression analysis will be utilized to find which variables have the strongest predictive tendencies amongst three index variables. Each of these three index variables is calculated to represent a department's use of community policing practices, investment in crime analysis strategies, and utilization of modern technologies. This research will employ United States Census data for the analysis of selected social disorganization variables and combine it with data from the Law Enforcement Management and Administrative Statistics (LEMAS) database and Uniform Crime Report (UCR) statistics.

This thesis includes four chapters following the introduction. Chapter 2 is a review of the literature, starting with a discussion of Social Disorganization Theory to provide a theoretical foundation for this research, followed by a discussion of the current research, effectiveness, and use of community policing, crime analysis, and modern policing technologies. The three research questions that will address a department's use of these three policing practices will also be introduced in Chapter 2, along with accompanying hypotheses. Chapter 3 presents the data and methods used in the study. Chapter 4 presents the analysis results and interpretation of the findings, and Chapter 5 is a discussion of the implications of the findings for police practice and policy, limitations of the research, and recommendations for future research.

Chapter 2: Crime and Police Practices in Socially Disorganized Areas

This chapter begins with an overview of the theoretical framework of Social Disorganization Theory, followed by a discussion of the research, effectiveness, and use of policing techniques such as community-oriented policing, crime analysis, and modern policing technologies. Based on the discussion, gaps in the literature are identified, which set the stage for the research questions and hypotheses that are presented at the conclusion of this chapter.

Crime in Disorganized Neighborhoods

Social Disorganization Theory and the research testing the theory have shown that crime is not necessarily a result of the people, but the places at which the crimes occur. Shaw and McKay (1942) took the concepts from Park and Burgess' Concentric Zones Theory and applied it to crime, finding that no matter who lived in the transitional zone around the epicenter of the city, there were still higher rates of crime (Akers & Sellers, 2013).

Shaw and McKay (1942) indicated that the higher prevalence of crime was due to the low socioeconomic status, high racial/ethnic heterogeneity, and highly transient nature of the residents of an area. They argued that disadvantaged neighborhoods comprised of many poor individuals, who were all more likely to come from a variety of racial and ethnic backgrounds, and, due to their lack of ties to the framework of these poor and diverse neighborhoods, moved out of the neighborhoods as soon as they were financially stable enough to do so. The convergence of these three social factors leads to a neighborhood having high levels of social disorganization. These three main components are still used in modern Social Disorganization Theory research, which will be discussed in succeeding paragraphs.

Based upon their findings, Shaw and McKay point to areas of high social disorganization lacking adequate levels of informal social controls, as a result of low socioeconomic status, high levels of ethnic/racial heterogeneity, and residential instability. In essence, Shaw and McKay (1942) came to the conclusion that it was the places, not the people, that fostered criminality (Hays, 2011).

Subsequent research testing Shaw and McKay's assertions found that high levels of social disorganization also lead to what was subsequently defined as a lack of informal social control (Sampson, Morenoff, & Earls, 1999; Sampson, Raudenbush, & Earls, 1997). Informal social controls are defined as the capacity of the individuals who reside in a certain community to regulate themselves (Sampson et al., 1997). Examples of these informal social controls provided by Sampson and colleagues (1997) include the monitoring of playgroups among children, the willingness to intervene to prevent acts such as truancy, and the confrontation of persons who are exploiting or disturbing public space.

Sampson et al. (1997) went on to further explain these lessened levels of informal social control through their principle of collective efficacy. Collective efficacy is defined as the social cohesion among neighbors combined with their willingness to intervene in criminal activity on behalf of the common good (Sampson et al., 1997). Their research went on to confirm their claim of collective efficacy, finding that collective efficacy successfully mediated the levels of concentrated disadvantage and residential instability in terms of violence.

It was not until Kornhauser's (1978) dissertation research until these informal social controls were more heavily emphasized with regards to Social Disorganization Theory research, leading to the modernization of social disorganization research.

Social Disorganization Theory Research

Once it was established that Social Disorganization Theory could be applied to general forms of crimes, expanding upon the juvenile delinquency that Shaw and McKay originally applied the theory to, academics attempted to expand their understanding of the complex measurements of social disorganization through the use of different forms of measurement of the three key variables outlined in Shaw and McKay's original research: socioeconomic status, ethnic/racial heterogeneity, and residential instability. Bursik (1988) summarized the topics associated with the original framework of Social Disorganization Theory as written by Shaw and McKay that needed revision, and the clarification of the measurements was a top priority. Since 1942, and especially since Bursik's publication in 1988, many researchers have tested the theory by constructing different measures of social disorganization in order to expand and clarify the theory. Through these developments, more in-depth information has been found, leading to deeper levels of confirmations of the original theoretical framework that outlines Social Disorganization Theory.

It has been found that socioeconomic status is an adequate predictor of homicide rates (Emerick et al., 2013; Rosenfeld, Baumer, & Messner, 2007), both social and physical disorder in communities (Sampson & Raudenbush, 1999), as well as higher rates of unsupervised peer groups and organizational (gang) participation (Sampson & Groves, 1989). Sampson and Groves (1989) subsequently link unsupervised peer groups and gang participation to higher violent crime rates and property crime rates. Social Disorganization Theory has also been expanded to the study of interpersonal violence between couples, analyzing the couple's socioeconomic status based on their status above or below the poverty line, receiving or not receiving public assistance, and their employment status (Browning, 2002). Browning (2002) concluded that participants with lower levels of socioeconomic status were more likely to be exposed to interpersonal partner violence.

Modern findings on the prevalence of a measure such as ethnic/racial heterogeneity in modern Social Disorganization Theory research is firm, finding that heterogeneous populations have a higher tendency to advocate unsupervised peer groups (Sampson & Groves, 1989), leading to higher crime rates. Furthermore, ethnic/racial heterogeneity has a positive correlation with violent crime rates when analyzed by street segments (Kim, 2018), as well as having a significant correlation with gang-related homicides within the Latino community (Emerick et al., 2014).

Ethnic and racial heterogeneity has also been an aspect of Social Disorganization Theory that has been tied to significant levels of collective efficacy (Sampson et al., 1997). In turn, this higher level of collective efficacy mediates the proficiency of violent crime in communities (Sampson et al., 1997).

The only lacking area of significant relationships drawn between ethnic/racial heterogeneity and crime has been regarding youth violent crime (Kaylen & Pridemore, 2000). Kaylen and Pridemore (2000) lacked findings supporting the claim that ethnic/racial heterogeneity leads to higher rates of violent crimes amongst youth.

Residential instability, reflecting the transient nature of the population described in Shaw and McKay’s (1942) original research, has been found to have strong correlations with homicide rates (Emerick et al., 2013). Residential instability has also been associated with the social and physical disorder in communities (Sampson & Raudenbush, 1999).

Through this development of the theoretical framework of Social Disorganization Theory, it is clear that there are many different ways to evaluate and analyze crime through a social disorganization lens. Through these different lenses, one thing is always undisputed:

Neighborhoods with higher levels of social disorganization experience more persistent problems regarding crime and delinquency.

Policing in Disorganized Neighborhoods

Research on Social Disorganization Theory provides supporting evidence to conclude that crime takes place differently in different types of locations, especially with different types of residents inhabiting these locations based on their socioeconomic status, racial/ethnic heterogeneity, and residential instability. Historically, however, police departments have conducted similar techniques in order to combat crime in their jurisdictions, with little consideration for the types of people that inhabited their jurisdiction, or the disorganization level of their jurisdiction to begin with (Choi et al., 2014). Scholars now refer to this practice of centralized policing techniques as the "Standard" model of policing (Weisburd & Eck, 2004).

Central policing practices of the standard model of policing include increasing the size of police departments, randomized patrol techniques, rapid response to calls for service, and generally applied intensive enforcement and arrests policies (Weisburd & Majmundar, 2018). Essentially, the standard model of policing is a model that provides a "one size fits all" approach to policing, allowing departments of any size, in any location, with an array of crime issues, to adopt and become effective (Weisburd & Eck, 2004; Weisburd & Majmundar, 2018).

The main drawback associated with the standard model of policing is that all of the police practices within the model are reactive, allowing crime to take place and simply responding to incidents after they occur (Weisburd & Majmundar, 2018). Measurement protocols of the model include evaluating the percentages of calls for service that were answered, patrols on the street at one time, and response times, all of which have not shown to reduce crime (Weisburd & Majmundar, 2018).

In the beginning of the 1990s, many scholars and practitioners agreed that the main reason that police officers were not combatting crime efficiently was because of the reactive nature of standard model police practices (Weisburd & Majmundar, 2018), leading to the advent of proactive policing measures aimed at stopping criminal behavior before it even occurred (Weisburd & Eck, 2004).

Working with Communities: Community Policing

The professional model resulted in a loss of trust between police departments and the civilians in which they were sworn to protect (Reisig & Parks, 2004). As a result, community policing (COP) techniques were employed in an attempt to address this breakdown of trust between police officers and the community (United States Department of Justice, Office of Community Oriented Policing Services, 2014a).

The main objective of the community policing model is to bolster the social ties between community members and the police departments (Bureau of Justice Assistance, 1994). COP strategies adhere to and embrace three core structural aspects: citizen involvement in identifying and addressing public safety concerns, the decentralization of decision making to allow for responses to be localized, and lastly, problem solving (Weisburd & Majmundar, 2018). According to the Office of Community Oriented Policing Services (United States Department of Justice, Office of Community Oriented Policing Services, 2014a), community policing is defined as “a philosophy that promotes organizational strategies, which support the systematic use of partnerships and problem-solving techniques, to proactively address the immediate conditions that give rise to public safety issues such as crime, social disorder, and fear of crime.” Through this definition, it is apparent that community policing is not a program that has a stringent set of rules and guidelines that must be followed, but a philosophy of policing to attempt to build community ties and combat crime at the same time (The Chief Justice Earl Warren Institute on Law and Social Policy, 2013; Weisburd & Majmundar, 2018). This attempt to build up the community ties, through involvement of community members in identifying public safety concerns (Weisburd & Majmundar, 2018), are the same types of community ties that are broken down in areas of high levels of social disorganization, resulting from a lack of social cohesiveness, informal social controls, and collective efficacy (Kornhauser, 1978; Sampson et al., 1997; Shaw & McKay, 1942). Community relations can be built back up in two different ways, either on an individual level, citizen by citizen, or on a group level, incorporating the support of neighborhood entities such as faith-based organizations, tenant counsels, business groups, local government agencies, social service providers, schools, and local businesses (The Chief Justice Earl Warren Institute on Law and Social Policy, 2013).

Kelling and Moore (1988) described community policing as a policing philosophy with end goals that are positive for both police officers and the community. Through community policing, police officers are able to use community members as another reference for data and information while community members have effective and open ways to express their concerns with local social issues (Goldstein, 1987). If community policing is properly executed, then the ties between the local police department and local community members will be strengthened, as well as strengthen social ties between residents, resulting in higher levels of collective efficacy and a stronger social structure throughout the jurisdiction.

This study utilizes the Law Enforcement Management and Administrative Statistics (LEMAS) 2012 database for a compilation of policing practices, such as community policing. Specific attributes included in the LEMAS database will be utilized in this study, and they are discussed in depth to follow.

To implement and show the importance of the community policing philosophy strategy, police organizations often start with changes to the agency's mission statement. Mission statements are key in police departments, as they give a broad overview of an agency's purpose, as well as describe the agency's intentions and roles within the community (FBI Law Enforcement Bulletin, 2000). Greene, Bergman, and McLaughlin (1994) discussed how combining departmental values with a formal mission statement is important for three reasons: (1) makes clear to those within and outside of the organization what the department values, (2) public pronouncements of mission statements provide a measurement tool in order to judge adequate policing, and (3) provides a formal basis for changing the informal culture of a public agency.

Although community policing has been recognized as one of the foremost policing philosophies that are utilized in modern American policing (Bureau of Justice Assistance, 1994; The Chief Justice Earl Warren Institute on Law and Social Policy, 2013), there is still not a general consensus as to what it is and how it works. McGuire, Kuhns, Uchida, and Cox (1997) found that there are different programs that are utilized in areas of rural populations compared to those utilized in urban populations. This is a prime example of how community policing is not a specific program with specific rules that must be followed, but more of a philosophy that should be applied toward policing efforts (The Chief Justice Earl Warren Institute on Law and Social Policy, 2013; Weisburd & Majmundar, 2018).

Sozer and Merlo (2013) stated that it is easier to implement community policing amongst areas with small populations compared to areas with larger populations. These findings were concluded through research that indicated that there is a broadened variety of community policing programs that have shown to work in rural areas (community contribution, problem-solving training, and problem-solving partnerships) compared to urban areas, where only problem-solving partnerships were found to have a significant difference.

Focusing Police Efforts: Crime Analysis

The International Association of Crime Analysts (IACA) defines crime analysis as:

> A profession and process in which a set of quantitative and qualitative techniques are used to analyze data valuable to police agencies and their communities. It includes the analysis of crime and criminals, crime victims, disorder, quality of life issues, traffic issues, and internal police operations, and its results support criminal investigation and prosecution, patrol activities, crime prevention and reduction strategies, problem-solving, and the evaluation of police efforts. (International Association of Crime Analysts, 2011)

Crime analysis plays a central role in the function of vast amounts of American police departments in modern society. Furthermore, crime analysis has been found to play a vital role in policing practices that are utilized throughout the country (Santos, 2014).

According to Weisburd and Majmundar (2018), crime reduction efforts become effective only once they are focused and targeted. In order for policing efforts to be focused and targeted, proper crime analysis must be utilized in order to collect information, process the statistics, and disseminate the information in the proper manner (Santos, 2014). Santos (2014) also stated that there is no research pointing to the effectiveness of crime analysis with regards to reducing crime due to the fact that the link between crime analysis and crime reduction is not direct; however, all policing practices that effectively reduce crime properly utilize crime analysis.

Santos (2014) argued that policing strategies that are found to be effective in the reduction of crime all rely on substantial crime analysis techniques in order to function properly.

She asserted that crime analysis is especially integral to hot spots policing and problem-oriented policing. Problem-oriented policing adopts the SARA method, all stages of which are dependent upon crime analysis. Hot spots policing is also dependent upon crime analysis, utilizing crime analysis products to determine hot spots that are in turn used by department command staff to assign directed patrol efforts (Santos, 2014).

Not only did Santos (2014) discuss the policing philosophies that are effective due to crime analysis, but she also discussed the policing philosophies that are ineffective due to their lack of necessity of crime analysis. An example of this is how the standard model of policing, which has been found inadequate with regards to crime reduction, utilizes crime analysis in a limited manner, only conducting simple cost analyses and evaluations of response rates (Santos, 2014).

Overall, the aforementioned research has shown that these policing approaches have been proven to be effective in one way or another with regards to reducing crime or disorder (Weisburd & Eck, 2004). It also shows that crime analysis is crucial in the proper implementation of all of these strategies (Santos, 2014), so one can conclude that police departments having crime analysis is essential to addressing crime problems.

Improving Policing: Modern Technology

Police departments in America have consistently been introducing new policing technologies throughout the past century in an effort to improve operational efficiency and outcomes, especially in times of diminished resources and increased police scrutiny (Strom, 2017). Recent hardware and software technology that has been introduced into American police departments are Gun Shot Detection (GSD) systems, License Plate Readers (LPRs), video surveillance measures, computerized databases, social media platforms, and Global Information

Systems (GIS) (Choi, Librett, & Collins, 2014; Koper, Taylor, & Woods, 2013; Kumar & Chandrasekar, 2011; Piza, Kaplan, Kennedy, & Gilchrist, 2014). Furthermore, technologies such as social media platforms, websites with reporting systems, and online citizen surveys have been used to improve relations between officers and the general public. These technologies have also been implemented to encourage citizen-officer communication and allow citizens to express their concerns in a legitimate manner to the police department, as well as report crime, if necessary (Ariel, 2017; Bertot, Jaeger, & Grimes, 2010; Beshears, 2018; Brainard & Derrick-Mills, 2011; Copitch & Fox, 2010). GSD systems, video surveillance technologies, and GIS have been used to address crime problems, allowing departments to utilize technology to not only to identify crime and crime patterns, but solve crime as well (Ariel, 2017; Beshears, 2017; Choi et al., 2014; National Institute of Justice, 1998; Piza et al., 2014; Shafique, Zahra, Farid, & Sharif, 2017; Shah & Braithwaite, 2013; Weisburd et al., 2015; Willis et al.,, 2018).

Use of technologies to assist police officers and detectives includes video surveillance purposes (Strom, 2017), starting with the use of Closed-Circuit Television (CCTV). CCTV has been found to help reduce crime alone; however, pairing CCTV technology with a proactive policing initiative has been found to not only enhance its crime reduction abilities (Piza et al., 2014), but also become more cost effective for police departments (Piza, Gilchrist, Caplan, Kennedy, & O'Hara, 2016). CCTV has also been found to be an effective crime reduction tool, especially when placed in areas with existing high crime rates (Shah & Braithwaite, 2013). Revolutionary to modern police forces, however, is the use of body-worn cameras (BWCs).

BWCs are small video camera devices that are to be worn on officers' uniforms during their shift, allowing every interaction that they make with other officers, and most importantly community members, to be recorded. The overall goal of BWCs is to help improve the high-quality public service expected of police officers and to promote the perceived legitimacy and sense of procedural justice that communities have about their police departments (Department of Justice Office of Community Oriented Policing Services, 2014b).

Research on BWCs has found that BWCs have accomplished this goal, lowering the odds of citizen complaints against officers (Ariel, 2017; Braga, Sousa, Coldren, & Rodriguez, 2018; White, Gaub, & Todak, 2017). Research also indicates that a majority of officers are not only open to wearing BWCs in hopes of helping relations with their communities (Jennings, Fridell, & Lynch, 2014), but those officers who wear BWCs have higher rates of arrests and citations issued compared to their non-BWC wearing counterparts (Braga et al., 2018).

One of the most prevalent uses of technologies in the 21st century revolves around the utilization of social media platforms by police departments. Utilization of social media platforms such as basic websites, electronic newsletters, online surveys, Facebook, Twitter, Instagram, and YouTube have all been found to have an effective impact regarding both community relations (Bertot et al., 2010; Beshears, 2017; Brainard & Derrick-Mills, 2011; Copitch & Fox, 2010) and crime solving (Beshears, 2017).

Studies go on to show how the use of social media may be difficult to introduce into modern police departments; however, effective community engagement through the use of social media platforms like the ones previously listed can have a positive impact on improving police-community relations (Copitch & Fox, 2010). Proper use of social media platforms on behalf of police departments has been found to enhance levels of transparency between the government and communities, leading to enhanced public relations (Bertot et al., 2010). Bertot and colleagues (2010) went even further to say that departments that are not utilizing social media platforms will lack trust within their communities.

Effective social media outlets that have been found to initiate positive communication between communities and the police departments that govern them are commonly accessible where "participation must be free and un-coerced" to exert a sense of "mutual fairness" (Brainard & Derrick-Mills, 2011, p. 387). Proper use of social media platforms has even been found to be successful in generating intelligence from the community (Strom, 2017), facilitating crime-solving aspects described by Beshears (2017).

GSD systems have also been utilized by police departments, mostly in response to the prevalence of firearm usage in the commission of crimes. GSD systems have proven effective in helping officers to identify and solve problems, as well as having a deterrent effect on crime if publication of the GSD systems has been announced (National Institute of Justice, 1998). GSD systems have been found to help improve police response and dispatch times to instances where firearms are used (Choi et al., 2014), and there has even been exploration into utilization of GSD systems in conjunction with police data and neighborhood features in order to assist in the identification of hot spots (National Institute of Justice, 1998). Research concluded that there is a direct association between the identification of hot spots using GSD systems and arrest rates in the identified locations (National Institute of Justice, 1998).

Overall, departments can use GSD systems in three ways: a rapid response tool, a problem-solving tool, as well as a crime prevention tool (National Institute of Justice, 1998, p. 2). Future uses of GSD systems revolve around combining the efforts of this technology with that of CCTV camera systems for enhanced shooter identification measures (Choi et al., 2014). The National Institute of Justice (1998) even claimed that the reason that firearm use in the commission of murders has held steady over the past few decades is due to the prevalence of GSD systems.

LPRs have been employed on a more consistent basis in recent years (Koper et al., 2013). LPRs are devices that automatically scan the license plates of cars and cross-reference these license plates against databases on stolen cars and other information, such as warrant databases. Although there has been relatively little research conducted evaluating the effectiveness of LPRs in the United States (Koper et al., 2013), there has been evidence indicating that they are effective in reducing crime (Koper et al., 2013; Willis et al., 2018), and have been an effective technology in combination with hot spots policing (Koper et al., 2013).

Not only has there been evidence regarding LPRs' effectiveness on reducing crime, but researchers have also found a lasting impact on the reduction of crime, even after the LPRs have been moved to other locations, creating a lasting crime reduction impact on the area (Koper et al., 2013). Overall, LPRs have been underused regarding their potential crime-solving capabilities, especially with regards to their possible uses in combination with other policing technologies in order to facilitate proper problem-oriented and hot spots policing techniques (Choi et al., 2014).

Regarding technologies associated with crime analysis, the pivotal technology that is crucial to focusing police efforts and assisting with proper crime analysis is GIS (Santos, 2017; Shafique et al., 2017). Weisburd (2015) stated that it is crucial to focus policing efforts on where crime happens, and GIS is the only technology that will properly assist departments in doing so. Also, Santos (2014) indicated that crime mapping (through the use of GIS) is crucial in order to develop proper hot spots to fuel hot spots policing efforts. GIS has also been found useful for crime analysis to occur, allowing for police personnel to identify possible crime locations, analyze past events, predict future events, as well as determine areas for personnel improvement

(Kumar & Chandrasekar, 2011). With the continual development and adoption of crime analysis in modern American police departments, it will foster future use of GIS in America.

All of the previously mentioned forms of technology have been found to assist in crime solving, as well as assist in developing relations with the community, one of the central tenants of community policing. Furthermore, applications such as GIS and other statistical software applications have allowed the crime analysis profession to evolve in the 21st century.

Research Questions

From the review of the research, there appears to be a gap in the understanding of how the relationship between how police carry out community policing, crime analysis, and implement advanced technology and the level of crime and social disorganization in the communities they serve. In the past, there have been multiple studies looking at how these three policing strategies are impacted by their community's level of social disorganization; however, there has been a lack of research evaluating all three of them together. This research attempts to fill this gap and evaluate them all together.

The overarching question that guides this research focuses on whether a community's level of social disorganization is related to how police departments are implementing community policing practices, crime analysis strategies, and using modern technologies to understand if departments are policing differently in different types of communities. To examine these relationships, the following three research questions will guide this study and subsequent empirical analysis:

Research Question 1: How does a community's level of social disorganization predict how police departments practice community policing?

Hypothesis 1.1: The higher the social disorganization levels of a community are, the more community policing techniques are implemented by the police department.

Hypothesis 1_0: There is no statistically significant relationship between social disorganization levels and the community policing practices of a police department.

Relations between the police and the community in areas of high levels of social disorganization are expected to be tense (Reisig & Parks, 2004; Sampson & Groves, 1989). A way that departments have found to address this tension and build relationships that will also be effective in dealing with crime and disorder is through the implementation of a community policing strategy (The Chief Justice Earl Warren Institute on Law and Social Policy, 2013; Weisburd & Eck, 2004). Community policing efforts have been found to increase the legitimacy amongst relationships between police departments and the citizens that they protect, as well as reduce crime when paired with a problem-oriented policing approach (Weisburd & Majmundar, 2018). How a police department invests in community policing is important and should be positively related to the level of social disorganization within a community because the higher the social disorganization levels are within a community, the more community policing strategies might be needed to make the ties with the community that are broken down in areas of high social disorganization.

Research Question 2: How does the community's level of social disorganization predict whether the police department has a crime analysis function?

Hypothesis 2.1: The higher the social disorganization levels of a community are, the more invested its police department is in crime analysis.

Hypothesis 2_0: There is no statistically significant relationship between social disorganization levels and the crime analysis practices of a police department.

Since areas of high social disorganization are expected to have higher crime rates, and research indicates that crime analysis is a vital aspect of all effective forms of effective crime reduction strategies (Santos, 2014), this research question examines how departments policing areas with different levels of social disorganization use crime analysis. The hypothesis is that the higher the levels of social disorganization are within a community, the more invested the department is in crime analysis because this is important in supporting effective crime reduction (Santos, 2014).

Research Question 3: How does a community's level of social disorganization predict how police use advanced technology?

Hypothesis 3.1: The higher the social disorganization levels are in a community, the more modern technology will be implemented by its police department.

Hypothesis 3_0: There is no statistically significant relationship between social disorganization levels and the use of modern technology on behalf of a police department.

Research has indicated that technologies such as GSD systems (Choi et al., 2014; National Institute of Justice, 1998), LPRs (Koper et al., 2013; Willis et al., 2018), GIS (Santos, 2014; Santos, 2017; Shafique et al., 2017; Weisburd, 2015), camera technology systems (Braga et al., 2018), and social media outlets have all been found to assist departments in improving their community relations as well as their crime reduction efforts. This research question examines how departments policing areas with different levels of social disorganization are utilizing modern policing technologies. It is hypothesized that there will be more use of modern technologies in areas of high social disorganization because of their higher crime and disorder rates (Reisig & Parks, 2004; Sampson & Groves, 1989) and the ability of the use of modern technology to combat these high crime and disorder rates.

Chapter 3: Data and Analytic Strategy

The purpose of this chapter is to describe the study's data as well as the analytical strategy used to answer the three research questions. The chapter will start with discussing the three sources of data used, followed by an outline of the analytic strategy, which discusses three statistical approaches that will be used to answer the research questions from the previous chapter. For this particular research venture, the sample population was targeted in order to capture a group of police departments that had a relatively homogenous population in terms of social disorganization levels. In order to do this, the sample population of this study includes only local police departments (not state, county, or tribal) that employ between 75 and 250 sworn officers.

Law Enforcement Management and Administrative Statistics (LEMAS)

The first data source is the Law Enforcement Management and Administrative Statistics (LEMAS) database. LEMAS databases are compiled through a survey of all departments in the country that employ more than 100 officers, as well as a nationally representative sample of all other departments in the country whose departments employ less than 100 officers.

Questionnaires are sent out to departments across the country that ask administrative personnel to provide information regarding topics such as, but not limited to, funding, personnel numbers, salary information, policing practices, and department protocols. LEMAS surveys were initially distributed in 1987 and have been periodically conducted every 3 to 6 years since then.

The 2012 LEMAS database is used in this study, which was the most recent year that was released at the initiation of this research venture. The 2012 survey was sent to a total of 3,472 agencies consisting of 2,613 local police departments, 810 sheriffs' offices, and 49 state agencies. Responses were submitted from 2,780 agencies that received questionnaires, resulting in an overall response rate of 80%. Response rates for the local police departments, sheriffs' offices, and state agencies were 82%, 74%, and 90%, respectively. This database was the key source for the ways in which police departments implement community policing practices, crime analysis strategies, and modern policing technologies.

United States Census Data

The second source of data is data from the United States Census Bureau (USCB). The USCB collects data on a decennial basis, starting in 1940. The United States Constitution mandates the Census and the overall goal of the Census is to provide information about the American population to legislatures in order to adjust political boundaries as well as apportion seats in the United States House of Representatives. The Census data provides Americans with information on the population in which they live, including information relevant to this study regarding social disorganization characteristics.

United States Census data was accumulated through manual compilation of statistics regarding social disorganization levels amongst cities in the United States. Each of the cities that was included in the final database (reference "Final Sample and Their Police Departments" section below for database framework techniques) was manually searched through "USA.com," an online source for United States Census data. "USA.com" was utilized for this study seeing as it aggregates census data on the city level, rather than the county or census-tract levels. The data that was compiled through this online web source was a compilation of data spanning the years of 2010-2014. Since this window includes the timeframe of the LEMAS data that was previously discussed (2012), this was a viable option to utilize to compile the social disorganization data.

Uniform Crime Report Data

The third data source for this research is the Federal Bureau of Investigation's (FBI) Uniform Crime Report (UCR). The first UCR was completed in 1930, and each subsequent UCR following this was compiled on an annual basis, amassing voluntarily submitted crime statistics from departments across the nation. The UCR program collects statistics on violent crime (i.e., murder and non-negligent manslaughter, rape, robbery, and aggravated assault) and property crime (i.e., burglary, larceny-theft, and motor vehicle theft), termed in totality as Part I crimes. By congressional mandate, arson was added to the list of Part I UCR offenses in 1979 (United States Department of Justice, Federal Bureau of Investigation, 2017).

UCR data for this study comes directly from the FBI's website. The UCR data that was applied to this study was for the calendar year 2012, as to align with the statistics collected from the two previously mentioned data sources.

Final Sample of Police Departments and Their Communities

The 2012 LEMAS survey resulted in a total of 2,826 police departments that responded. For the purposes of this study, local police departments, that were not tribal, were selected. In addition, suburban local police departments with full-time, sworn officers between 75 and 250 were selected in order to include departments with adequate resources to incorporate the three policing practices of interest: community policing, crime analysis, and modern policing technologies. These departments were also targeted in order to capture a relatively homogeneous population in terms of social disorganization levels as well as a fairly consistent population within each jurisdiction.

Of these 2,826 respondents to the LEMAS survey, 2,059 of them were local police departments, and of the 2,059 local police departments, all but 23 were not tribal, resulting in

2,036 cases. Once only departments with between 75 and 250 officers were selected, there was a resulting caseload of 469 cases.

Because these are local police departments, they serve a specific city or town, thus the 469 jurisdictions that are served by these departments were searched in ‘“‘USA.com” to collect Census data regarding selected variables to represent social disorganization characteristics of the community. Twenty-nine jurisdictions did not return results, indicating that they did not report their statistics to “USA.com,” leading to these cases being dropped from the study due to the lack of social disorganization characteristics.

Lastly, UCR statistics were gleaned from the FBI’s website. Of the 440 remaining police departments, there was a loss of 22 cases due to the lack of crime statistics recorded in the UCR, indicating that these 22 cases did not report their crime statistics to the FBI. Thus, the final dataset contained 418 police departments.

Control Variables

Control variables are variables that are kept constant in order to prevent confounding with the independent variables in the study. For this study the control variables are:

- Number of Sworn Officers (FTSworn): the number of full-time sworn officers within a department (source: LEMAS)
- Median Age (MedAge): the median age of the population of the jurisdiction (source: Census)
- Median House Value (MHV): the median house value of all residences within the jurisdiction (source: Census)
- Population Density (PopDen): the population density of the jurisdiction, calculated by population per square mile (source: Census)

- Violent Crime Rate (VCR): the violent crime rate of the jurisdiction[1] (source: UCR)
- Property Crime Rate (PCR): the property crime rate of the jurisdiction[1] (source: UCR)

Independent Social Disorganization Variables

These independent variables are measures of social disorganization selected based on previous research on Social Disorganization Theory. The five variables, presented below, are an attempt to mirror the original measures of social disorganization levels that were utilized by Shaw and McKay (1942): socioeconomic status, racial/ethnic heterogeneity, and transient populations.

- Percent Non-White (%Non-White): the percentage of the population of the jurisdiction that is not white (Caucasian) (source: Census)
- Percent of the Population[2] in Poverty (PopPov): the percentage of the population of the jurisdiction below the poverty line (source: Census)
- Percent of the Population Unemployed (%Unemployed): the percentage of the population of the jurisdiction that is unemployed (source: Census)[3]
- Percentage of Vacant Housing Units (%Vacant): the percentage of the residences in the jurisdiction that are vacant (source: Census)
- Percentage of Rented Housing Units (%Rented): the percentage of the residences in the jurisdiction that are rented (source: Census)

[1] Crime rates calculated per 10,000 residents

[2] In comparison to the percentage of families that are in poverty, another variable accessible on "USA.com"

[3] %Unemployed=MaleUnem + FemaleUnem / Pop_M + $Pop_{F;}$ whereas "MaleUnem" and "FemaleUnem" are the two unemployment rates of each gender, divided by the overall population of each gender.

Socioeconomic status is one of the three main tenants that construct the theoretical framework of what defines social disorganization. However, especially in the modern era of data collection, there are multiple ways to collect this data. Researchers have now utilized data such as percentages of the population under the poverty line (Barnett & Mencken, 2002; Browning, 2002; Goodson & Bouffard, 2017; Kaylen & Pridemore, 2000; Kim, 2018; Osgood & Chambers, 2000; Przeszlowski & Crichlow, 2018; Rogeczi & Jarvis, 2013; Rosenfeld et al., 2007; Sampson & Raudenbush, 1999; Steidley, Ramey, & Shrider, 2017; Warner & Pierce, 1993), as well as the percentage of the population on public assistance (Browning, 2002; Emerick, Curry, Collins, & Rodriguez, 2013; Sampson & Raudenbush, 1999), in order to collect information regarding the socioeconomic status of an area. Measures of socioeconomic status have also been expanded to include measures of unemployment rates (Barnett & Mencken, 2002; Browning, 2002; Emerick et al., 2013; Rogeczi & Jarvis, 2013; Rosenfeld et al., 2007; Sampson & Raudenbush, 1999; Steidley et al., 2017) as well as the utilization of education level as a proxy for socioeconomic status (Emerick et al., 2013; Kim, 2018; Sampson & Groves, 1989; Steidley et al., 2017). Barnett and Mencken (2002) also explored the utilization of official income inequality statistics as a part of an index measure in order to collect data on socioeconomic status.

Regarding the measure of ethnic and racial heterogeneity amongst populations, there has also been a recent expansion of types of data that is used to collect this information. Modern researchers are now expanding their data collection to items such as the utilization of an index variable, $1- \Sigma pi^2$ (Goodson & Bouffard, 2017; Kaylen & Pridemore, 2000; Osgood & Chambers, 2000; Sampson & Groves, 1989; Warner & Pierce, 1993), as well as the utilization of a modified Herfindahl Index (Kim, 2018) in order to calculate ethnic/racial heterogeneity. Other measures include the analysis of the percentage of the population that is foreign born (Browning, 2002;

Przeszlowski & Crichlow, 2018; Sampson & Raudenbush, 1999), Latino (Browning, 2002; Sampson & Raudenbush, 1999), Black or African-American (Browning, 2002; Przeszlowski & Crichlow, 2018), or Non-white (Barnett & Mencken, 2002).

Measures of residential instability correlating with the nature of a transient population that Shaw and McKay adapted from Park and Burgess' Concentric Zones Theory has also been expanded in recent years. Researchers now utilize data such as the population of residents who has moved residences within the past 15 years (Browning, 2002), the past 5 years (Kaylen & Pridemore, 2000; Osgood & Chambers, 2000; Warner & Pierce, 1993), as well as the past year (Goodson & Bouffard, 2017). Other measures of residential instability include residents within a 15-minute walk of their childhood home (Sampson & Groves, 1989), average length of residence (Kim, 2018), and population change over a span of 10 years (Barnett & Mencken, 2002).

However, perhaps some of the most relevant and modern measures of residential instability include measures of the percent of vacant residences (Emerick et al., 2013), percent of rented residences (Rogeczi & Jarvis, 2017; Steidley et al., 2017), and the percentage of owner-occupied residences (Emerick et al., 2013).

Overall, crime has been evaluated based on social disorganization levels in many different ways since the advent of Social Disorganization Theory by Shaw and McKay in 1942. All three of the central tenants of Social Disorganization Theory, socioeconomic status, ethnic/racial heterogeneity, and residential instability, have continually developed into more clear and concise variables of analysis, answering the criticisms of Bursik (1988).

Dependent Variables

There are three dependent variables to address the three research questions and represent a police department's implementation of community policing, crime analysis, and technology. Each dependent variable is a composite measure created from questions on the LEMAS survey.

Community Policing (COP). In order to properly evaluate a police department's utilization of community policing techniques, 10 LEMAS variables are combined into a community policing index variable. The LEMAS study asks departments about important facets of community policing, such as whether or not they incorporate community policing into a mission statement, their community policing-based training activities, SARA initiatives, as well as topics such as community partnerships and consistency in the geographic deployment of patrol officers.

Each question was coded 1 for "yes" and 0 for "no":

(1) Community policing component included in written mission statement

(2) At least 8 hours of training for recruits on community policing issues[4]

[4] The question asked "During the 12-month period ending December 31, 2012, what proportion of FULL-TIME SWORN PERSONNEL received at least 8 hours of training on COMMUNITY POLICING issues (e.g., problem solving, SARA, and community partnerships)? Check one for both 'a' (Recruit training) and 'b' (In-Service training)." Answers of "all officers" or "more than half" of the officers having completed the 8 hours of training will be assigned a value of "1," correspond with a "Yes" answer. Respondents who answered saying that either "less than half" or "none" of their officers received 8 hours of training will be assigned a value of "0," corresponding with an answer of "No."

(3) At least 8 hours of in-service community policing training for patrol officers[4]

(4) SARA-type problem-solving projects actively engaged in by patrol officers

(5) Evaluation criteria for patrol officers involves collaborative problem-solving projects

(6) Problem-solving partnership or written agreement with any local civic, business, or governmental organization

(7) Same patrol officers regularly assigned responsibility for same areas or beats

(8) Utilized information from a survey of local residents about crime, fear of crime, or satisfaction with law enforcement

(9) Public can report crimes through email or texting

(10) Public can receive information by email or texting

Responses to these survey questions, with the exception of items 2 and 3 on this list, resulted in answers of either “Yes” or “No.” correlating with a numerical value of “1” or “0” in order to make community policing operational.

Crime Analysis (CA). The LEMAS survey asks police departments about the type and number of crime analysts that a department employs. LEMAS first asks respondents:

> “F7. During the 12-month period ending December 21, 2012, WHO conducted RESEARCH OR STATISTICAL ANALYSES (including geospatial analyses) using your agency’s computerized records of criminal incidents?”

Respondents answer whether they have internally sourced their crime analysts or whether crime analysis is conducted externally to the department (i.e., through private companies, external government entities, or college/universities). If the respondents answer that they have internal crime analysis practices, then the respondents proceed to a secondary question asking:

F8. If YES to F7a[5], during the 12-month period ending December 31, 2012, how MANY personnel conducted RESEARCH OR STATISTICAL ANALYSES using your agency's computerized records of criminal incidents? If none, enter '0'.

The four answers that a number of crime analysts will be provided are (1) full-time, non-sworn, (2) full-time, sworn, (3) part-time, non-sworn, and (4) part-time, sworn. For each of these four possibly internally sourced personnel types, a number will be inserted stating the amount of said type of personnel is employed through the department.

In an attempt to represent the importance that a department places on its use of crime analysis, a weighted scores system is used. The weighted scores system places the most importance on full-time, non-sworn crime analysts, because this shows the commitment of resources to crime analysis since the department has gone to an external source to hire and fill a new position as well as invest funding for benefits and retirement for an entirely new position. The next level of importance is placed on a full-time, sworn analyst, seeing as this shows the department has invested enough into crime analysis that it has removed an officer from patrol and/or other duties in order to conduct crime analysis. The following two were placed at the bottom of the weighted scores system due to the fact that they are part-time, compared to full-time, positions. Part-time, non-sworn analysts are given the third strongest weight, as they are an external hire, and part-time, sworn analysts are given the fourth strongest weight, depicting the least amount of investment in crime analysis on behalf of the department.

The weighted values are as follows: full-time, non-sworn analyst: 1.1; full-time, sworn crime analyst: 1.0; part-time, non-sworn analyst: 0.55; and part-time, sworn analyst: 0.50. These

[5] Indicating that their crime analysis was internally sourced within the department.

relative weight values are intended to put slightly more emphasis on having non-sworn personnel in comparison to sworn personnel.

Seeing as part-time is perceived as half of full-time, even if it is not always, part-time analysts are assigned half the weighted value as their full-time counterparts, resulting in values of 0.55 and 0.50. This process uses the same relative weight as used to distinguish civilian and sworn analysts.

In order to study the emphasis of crime analysis of the department relative to the size of the agency, we will also compute the previously mentioned weights into a rate variable, utilizing O'Shea and Nicholls' (2002) recommendation of one crime analyst per 100 police officers. The equation for the rate variable will be as follows[6]:

$$F8e(1.10)+F8a(1.0)+F8d(0.55)+F8b(0.5) \ / \ \text{Number of Officers} \times 100$$

A value that is over "1.0" means adequate staffing according to industry standards, and one less than 1.0 means inadequate staffing (O'Shea & Nicholls, 2002). This variable will have no particular range; however, this threshold value of "1.0" will be used in order to determine adequate or inadequate staffing of crime analysts on behalf of a department.

Modern Technology (TECH). The third dependent variable was created from the 2012 LEMAS database, combining yes answers to six questions related to having certain types of technology. They include:

(1) Utilized gunshot detections systems

(2) Utilized license plate readers

(3) Utilized video surveillance of public areas

[6] "F8" refers to the LEMAS question assigned number; "e, a, d, b" refer to the answer codes for question "F8", one for each type of internally sourced crime analyst.

(4) Utilized video cameras in patrol vehicles

(5) Utilized video cameras on patrol officers

(6) Utilized video cameras on weapons

The range of the technology index is 0 and 6. Overall, higher values mean that the department is more invested in modern technologies compared to a department with a lower score.

Analytic Strategy

The purpose of this section is to discuss and outline the analytic strategy that was utilized in this study in order to answer the three research questions. The analysis will start with simple descriptive statistics, followed by correlation analysis, and then three separate models of Backwards Stepwise Regression analysis in order to answer the three research questions.

Descriptive statistics are conducted to provide useful information about the nature of the data (Wilcox, 2009, p. 9). Measures of central tendency will be used to see the nature of the individual variables prior to the correlation and regression analyses, as all variables are ratio-style variables. Those include computing values such as the mean, median, variance, skewness, and kurtosis values for each variable (Wilcox, 2009, p. 12).

Correlation analyses are conducted to examine bivariate relationships between all variables in the study. It is important to test for multicollinearity in order to test for relationships between the independent variables in a study because multicollinearity will affect the future results of the regression analysis and can limit the conclusions that can be drawn from the findings (Henry M. Jackson Foundation, National University, 2017).

Backward stepwise regression analysis is used to test the relationship between each dependent variable (COP, CA, and TECH) and the control and independent variables. Backward stepwise regression involves conducting an initial multiple regression model and eliminating independent variables one at a time based on their significance to the model. Initially, all predictor (independent) variables are placed in the model and then their significance to the model is calculated using t-test results for each predictor. If the predictor meets the removal criterion, then it is removed, and the remaining predictor variables are recalculated and produce a subsequent regression model (Field, 2009). These steps are taken until the most significant independent variables remain, all of which have been tested against the removal criterion.

Chapter 4: Results

In this chapter, the results of the descriptive statistics analysis are presented, followed by the correlation results, and finally the results of the regression analyses are presented. Issues regarding multicollinearity of the independent variables are also presented in this chapter.

Descriptive Statistics Results

Table 1 shows the descriptive statistics of the five social disorganization variables of the study: “Percentage of the Population Non-White,” “Percentage of Vacant Households,” “Percentage of Rented Households,” “Percentage of the Population in Poverty,” and “Percentage of the Population Unemployed.”

Table 1

Social Disorganization Theory Descriptive Statistics

						Skewness		Kurtosis	
Variable	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**	**Variance**	**Statistic**	**St. Error**	**Statistic**	**St. Error**
%Non-White	6.00	96.00	31.24	17.88	319.64	1.06	0.12	0.86	0.24
%Vacant	2.40	47.70	10.44	6.42	41.25	2.08	0.12	6.3	0.24
%Rented	9.49	73.31	39.33	11.04	121.92	0.23	0.12	0.13	0.24
PopPov	3.02	41.60	17.59	8.26	68.25	0.48	0.12	-0.34	0.24
%Unemployed	4.01	26.33	9.93	3.40	11.59	0.84	0.12	1.12	0.24

Social Disorganization. According to the results regarding the percentage of the populations who were Non-white, there was a minimum value of 6% and a maximum value of 96%, resulting in a range of 90. The mean percentage of Non-whites in a population was 31.24% with a standard deviation of 17.87%, representing the average distance from the mean of the communities in the study. The variance of the percentage Non-white data was 319.64, indicating a very spread out data distribution. The skewness value for percentage Non-white was 1.06, representing a slightly positive, or right, skew about the mean of the data. The kurtosis value of 0.86 represents a slightly leptokurtic distribution.

Of the cities in the study, the percentage of vacant households ranged from 2.40% to 47.70%, resulting in a range of 45.30. The mean percentage of vacant households was 10.44%, with a standard deviation of 6.42, exhibiting the average distance from the mean of all of the responses. With a variance value of 41.25, this shows that the data for the percentage of vacant households were spread out. The skewness value for the percentage of vacant households was 2.08, representing a slightly positive, or right, skew about the mean of the data. The kurtosis value of 6.30 represents a leptokurtic distribution. Pertaining to the percentage of rented households of the communities included in the study, there was a minimum percentage of 9.49% and a maximum percentage of 73.31%, resulting in a range of 63.82. The mean percentage of rented households was 39.33%, with a standard deviation of 11.04, exhibiting the average distance from the mean of the responses. The variance of the percentage of rented households was 121.92, exhibiting a spread out distribution of the data. The skewness value of 0.23 indicates a very slight positive skew in the data, with a kurtosis value of 3.40, indicating a slightly leptokurtic distribution.

The percentages of unemployment of the communities in the study ranged from a minimum percentage of 4.01 to a maximum percentage of 26.33, resulting in an overall range of 22.32. The mean percentage of unemployment was 9.93%, with a standard deviation of 3.40, exhibiting the average distance from the mean of the responses. With a variance statistic of 11.59, this shows that the data for the unemployment percentages was the least spread data distribution out of the measurements for social disorganization. For the percentage of the population that was unemployed, there was a skewness value of 0.84 and a kurtosis value of 1.12. These values indicate a very slightly positive, or right, skew, and slightly leptokurtic distribution amongst these values, respectively.

Regarding the statistics for the percentages of the population in poverty of the cities in the study, there was a minimum percentage of 3.02 and a maximum percentage of 41.60, resulting in a range of 38.58. The mean percentage of the population in poverty was 17.59, with a standard deviation of 8.26, indicating the average distance from the mean of this data. The variance of the data was 68.25, indicating a spread out distribution, with a skewness value of 0.48 and a kurtosis value of -0.34. These statistics indicate that the distribution for the percentage of the population in poverty was slightly positive, or right, skewed, as well as slightly platykurtic, respectively.

Table 2

Control Variables Descriptive Statistics

						Skewness		Kurtosis	
	Minimum	**Maximum**	**Mean**	**Standard Deviation**	**Variance**	**Statistic**	**St. Error**	**Statistic**	**St. Error**
VCR	0.80	277.40	32.90	26.54	704.54	2.88	0.12	18.37	0.24
PCR	5.50	1127.60	265.85	140.81	19828.04	1.17	0.12	3.20	0.24
FT Sworn	75	250	135.96	42.45	1802.07	0.68	0.12	-0.33	0.24
PopDen	231.74	53015.46	3754.06	4267.61	18212507.05	6.03	0.12	55.14	0.24
MHV	11,200.00	1,000,001.00	230,927.82	160,889.57	2.589xE^{10}	2.12	0.12	5.54	0.24
MedAge	18.00	52.50	35.81	4.67	21.83	-0.11	0.12	0.72	0.24

Control Variables. The first control variable, shown in Table 2 above, is the violent crime rate. The violent crime rate had a minimum value of 0.8 with a maximum value of 277.40, resulting in a range of 276.60. The mean violent crime rate was 32.90, with a standard deviation of 26.54, representing the average distance from the mean of all the values in the distribution. The variance of 704.54 indicates a spread out distribution, and the skewness value of 2.88 and kurtosis value of 18.37 represents a positive (right) skewed and leptokurtic distribution.

For the property crime rate, we had a minimum value of 5.50 and a maximum value of 1,127.60, resulting in a range of 1,122.10. The mean property crime rate was 265.85, with a standard deviation of 140.81 representing the average distance of each value in the distribution from the mean. The variance value of 19,828.04 represents an incredibly spread out distribution. There is also slightly positive (right) skew and leptokurtosis in the distribution with skewness and kurtosis values of 1.17 and 3.20, respectively.

The minimum of 75 and maximum of 250 officers were expected in terms of the range for the number of full-time, sworn personnel, seeing as it was one of the parameters for inclusion in the final database. The mean number of full-time, sworn personnel was 135.96, with a standard deviation of 42.45, representing the average distance from the mean of all the values in the distribution. The distribution of full-time, sworn personnel was very spread out, as well as very slightly positively skewed and platykurtic, with values of 1,802.07, 0.68, and -0.33, respectively.

The population density values had a minimum value of 231.74, and a maximum value of 53,015.46, resulting in an overall range of 52,783.72. The mean population density was 3,754.06, with a standard deviation of 4,267.61, representing the average distance of all values from the mean of the distribution. The variance value of 18,212,507.05 is incredibly high, showing that the distribution is incredibly spread out. Not only is the distribution spread out, but also positively (right) skewed and highly leptokurtic, with values of 6.03 and 55.14, respectively.

The median house value has a minimum cost of 11,200.00 and a maximum value of 1,000,001.00 dollars, resulting in a range of 988,801.00. The mean median house value was 230,927.82 dollars, with a standard deviation of 160,889.57, representing the average distance from the mean of each of the values in this distribution. The distribution also appears to be positively (right) skewed and slightly leptokurtic, seeing as the skewness and kurtosis values are 2.12 and 5.54, respectively.

The minimum median age was 18.00 years old, with the maximum median age coming in at 52.50, resulting in a range of 34.50. The mean median age was 35.81, with a standard deviation of 4.67, representing the average distance from the mean of each value in this distribution. It also appears that this distribution is slightly spread out, negatively (left) skewed, and platykurtic based on the variance, skewness, and kurtosis values of 21.83, -0.11, and 0.72, respectively.

Table 3

Indexes Descriptive Statistics

						Skewness		Kurtosis	
	Minimum	**Maximum**	**Mean**	**Standard Deviation**	**Variance**	**Statistic**	**St. Error**	**Statistic**	**St. Error**
COP	0	10	6.17	2.13	4.54	-0.37	0.12	-0.15	0.24
CA	0	65	4.49	8.18	66.86	4.32	0.12	21.72	0.24
TECH	0	6	2.44	1.09	1.18	0.14	0.12	-0.08	0.24

Community Policing. The community policing index was comprised of 10 different items on the 2012 LEMAS survey that were added together to tell how invested a particular department was in community policing practices. A table of these 10 items and the frequencies of their responses are included in Appendix A. As shown in Table 3, the minimum community policing index value was 0, with a maximum of 10, resulting in an overall range of 10. The mean score for the community policing index was 6.17, meaning that on average, departments in the study had participated in just over six of the 10 practices included in the index. The standard deviation of the data is 2.13, representing the average distance from the mean of each of the values in this distribution. With a variance value of 4.54, a skewness value of -0.37, and a kurtosis value of -0.15, it can be seen that this distribution is condensed, negatively (left) skewed, and slightly platykurtic.

Crime Analysis. The crime analysis index was calculated using a weighted scoring system of each of the four different types of employment on behalf of crime analysts in the LEMAS database. The goal of this weighted system was to place emphasis on certain types of positions compared to others, in hopes of accurately representing the amount of investment that a department had in crime analysis strategies. The full descriptive statistics of each of these four different employment types for crime analysts can be found in Appendix A.

The results of this analysis show that the minimum crime analysis index score was 0, and the maximum crime analysis index was 65. With a mean score of 4.49, it is apparent that, on average, departments in the study had any combination of crime analysis positions that exemplified between four and five crime analysts. The standard deviation value of 8.18 shows the average distance from the mean of each of the scores in this distribution. According to the variance level of 66.86, the skewness value of 4.32, and the kurtosis value of 21.72, it is concluded that the distribution of crime analysis index scores is very spread out, positively (right) skewed, and highly leptokurtic.

Modern Technology. The modern technology index was calculated similarly to the community policing index, just with six values from the 2012 LEMAS database instead of 10. A full table listing each of these six variables and the frequencies of each of their responses is available in Appendix A. In terms of the index overall, the minimum value was 0, with a maximum value of 6. The mean index score was 2.44, indicating that on average, each police department utilized between two and three of the modern technology applications that were included in the index. The standard deviation of 1.09 shows the average distance from the mean of each of the responses in this distribution. Based on the variance value of 1.18, the skewness value of 0.14, and the kurtosis value of -0.18, it is concluded that this distribution is fairly condensed, very slightly positively (right) skewed, and very slightly platykurtic.

Correlation Results

Before moving on to the results of the Backwards Linear Regression models to answer the three research questions, it is first important to evaluate all variables based on the correlations between them. It is important to analyze these results in order to test for multicollinearity within the independent variables, so as to not impact the integrity of your study (Henry M. Jackson Foundation, National University, 2017). The correlations between each variable in this study can be found in Table 4.

Table 4

Pearson Correlation

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 %Non-White	P.Corr	1.00	.20**	.30**	.56**	.34**	.31**	0.02	0.07	.23**	0.02	-.14*	-0.07	0.07	-0.02
	Sig.		0.00	0.00	0.00	0.00	0.00	0.71	0.13	0.00	0.62	0.00	0.17	0.17	0.63
2 %Vacant	P.Corr	.20**	1.00	-0.08	.46**	.45**	.19**	0.03	-0.03	-.110*	-.32**	.16**	-0.07	-0.02	0.07
	Sig.	0.00		0.11	0.00	0.00	0.00	0.50	0.60	0.03	0.00	0.00	0.18	0.63	0.14
3 %Rented	P.Corr	.30**	-0.08	1.00	.24**	.53**	.21**	0.05	0.03	.43**	.17**	-.54**	-0.07	-0.01	-0.09
	Sig.	0.00	0.11		0.00	0.00	0.00	0.31	0.51	0.00	0.00	0.00	0.17	0.82	0.06
4 %Unemployed	P.Corr	.56**	.46**	.24**	1.00	.61**	.50**	.17**	0.02	.11*	-.28**	-0.06	-0.09	-0.01	-0.09
	Sig.	0.00	0.00	0.00		0.00	0.00	0.00	0.63	0.03	0.00	0.21	0.06	0.76	0.08
5 PopPov	P.Corr	.34**	.45**	.53**	.61**	1.00	.44**	.23**	-0.03	0.02	-.43**	-.54**	-.12*	-0.06	0.02
	Sig.	0.00	0.00	0.00	0.00		0.00	0.00	0.58	0.73	0.00	0.00	0.02	0.25	0.70
6 VCR	P.Corr	.31**	.19**	.21**	.50**	.44**	1.00	.64**	.41**	0.01	-.22**	-.23**	-0.01	0.07	0.00
	Sig.	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.78	0.00	0.00	0.87	0.14	0.95

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Table 4 Continued

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
7 PCR	P.Corr	0.02	0.03	0.05	.17**	.23**	.64**	1.00	.58**	-.17**	-.17**	-.22**	0.09	0.03	0.05
	Sig.	0.71	0.50	0.31	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.06	0.54	0.29
8 FTSworn	P.Corr	0.07	-0.03	0.03	0.02	-0.03	.41**	.58**	1.00	0.02	0.04	-0.05	.13**	0.04	.14**
	Sig.	0.13	0.60	0.51	0.63	0.58	0.00	0.00		0.67	0.40	0.31	0.01	0.37	0.01
9 PopDen	P.Corr	.23**	-.11*	.43**	.11*	0.02	0.01	-.17**	0.02	1.00	.27**	-0.06	-.14**	0.02	-0.06
	Sig.	0.00	0.03	0.00	0.03	0.73	0.78	0.00	0.67		0.00	0.24	0.00	0.62	0.20
10 MHV	P.Corr	0.02	-.32**	.17**	-.28**	-.43**	-.22**	-.17**	0.04	.27**	1.00	.19**	0.06	.10*	-0.08
	Sig.	0.62	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00		0.00	0.24	0.04	0.11
11 MedAge	P.Corr	-.14**	.16**	-.54**	-0.06	-.54**	-.23**	-.22**	-0.05	-0.06	.19**	1.00	0.03	0.04	-0.06
	Sig.	0.00	0.00	0.00	0.21	0.00	0.00	0.00	0.31	0.24	0.00		0.49	0.43	0.24
12 COP	P.Corr	-0.07	-0.07	-0.07	-0.09	-.12*	-0.01	0.09	.13**	-.14**	0.06	0.03	1.00	.11*	.14**
	Sig.	0.17	0.18	0.17	0.06	0.02	0.87	0.06	0.01	0.00	0.24	0.49		0.03	0.00
13 CA	P.Corr	0.07	-0.02	-0.01	-0.01	-0.06	0.07	0.03	0.04	0.02	.10*	0.04	.11*	1.00	0.06
	Sig.	0.17	0.63	0.82	0.76	0.25	0.14	0.54	0.37	0.62	0.04	0.43	0.03		0.25
14 TECH	P.Corr	-0.02	0.07	-0.09	-0.09	0.02	0.00	0.05	.14**	-0.06	-0.08	-0.06	.14**	0.06	1.00
	Sig.	0.63	0.14	0.06	0.08	0.70	0.95	0.29	0.01	0.20	0.11	0.24	0.00	0.25	

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Salkind (2011) outlined parameters for the evaluation of correlation results in terms of their strength. The parameters are as follows:

+/- 0.8 – 1.0 – very strong relationship

+/- 0.6 – 0.8 – strong relationship

+/- 0.4 – 0.6 – moderate relationship

+/- 0.2 – 0.4 – weak relationship

+/- 0.0 – 0.2 – very weak relationship

With these parameters in mind, there are a total of 17 very weak relationships, 13 weak relationships, 12 moderate relationships, two strong relationships, and zero very strong relationships between the variables in the study.

Overall, there are 17 very weak correlations according to Salkind (2011). However, none of these relationships is statistically significant, so there is no further discussion provided for these relationships.

Overall, there were a total of 13 statistically significant, weak correlations between variables in this study, having a correlation coefficient somewhere between +/- 0.2 and +/- 0.4, as stated by Salkind (2011). Of these 13 relationships, there were five involving the percent Non-white variable. The first correlation was between the percentage of the population that was Non-white and the percentage of vacant households in the location, with a correlation coefficient of 0.20 ($p = 0.00$). The second relationship was between the percentage of the population that was Non-white and the percent of rented households in the location, with a correlation coefficient of 0.30 ($p = 0.00$). The last three correlation coefficients involving the percentage of the population that was Non-white were between the percentage of the population in poverty, the violent crime rate, and the population density of the locations. These relationships resulted in correlation coefficients of 0.34 ($p = 0.00$), 0.31 ($p = 0.00$), and 0.23 ($p = 0.00$), respectively. These relationships indicate that as the percentage of the population that is Non-white rises, then so does the percentage of both vacant and rented households, the percentage of the population in poverty, the violent crime rate, and the population density.

On top of its weak correlation with the percentage of the population that is Non-white, as stated in the previous section, the variable for the percentage of rented households in a location had two more statistically significant, weak correlations with other variables in this study. The first relationship was with the percentage of the population that was unemployed, with a correlation coefficient of 0.24 ($p = 0.00$), and the second correlation was with the violent crime rate, with a correlation coefficient of 0.21 ($p = 0.00$). Both of these relationships are to be expected. The first relationship indicates that as the percentage of unemployed people rises, so does the amount of rented households in the given location. The second relationship indicates that as the population of rented households rises, so does the violent crime rate, potentially exhibiting a lack of informal social controls in a transient population.

The property crime rate was also significantly weakly correlated to the percentage of the population in poverty with a correlation coefficient of 0.23 ($p = 0.00$). This correlation is as to be expected, indicating that as the population in poverty rises, so does the property crime rate, implying that those in need commit property crimes to get the goods they need to survive.

The median house value measurement showed four statistically significant weak relationships, with the percentage of vacant households, the percentage of the population that was unemployed, the violent crime rate, and the population density. Each of these correlations resulted in correlation coefficients of -0.32 ($p = 0.00$), -0.28 ($p = 0.00$), -0.22 ($p = 0.00$), and 0.27 ($p = 0.00$), respectively. Each of these relationships is as to be expected, indicating that as the median house value goes up, the percentage of vacant households, the percentage of the population that is unemployed, and the violent crime rate go down, and the population density rises.

Two of the 13 significant weak relationships involved the median age control variable, exhibiting correlations with both the violent crime rate and the property crime rate. These relationships show correlation coefficients of -0.23 (p = 0.00) and -0.22 (p = 0.00), respectively. Each of these relationships is to be expected, indicating that as the median age rises, then both the violent and property crime rates go down.

Twelve of the statistically significant correlations are designated moderate relationships by Salkind (2011), possessing a correlation coefficient between +/- 0.4 and +/- 0.6. Two of these correlations involve the percentage of the population that is unemployed statistic, the first being with the percentage of the population that is Non-white, and the second with the percentage of vacant households in the location. These correlations resulted in coefficients of 0.56 (p = 0.00) and 0.46 (p = 0.00), respectively. These relationships indicate that as the percentage of the population that is unemployed rises, so do the percentage of the population that is Non-white and the percentage of the households that are vacant.

The next two significantly moderate correlations involve the percentage of the population that is in poverty, showing moderate relationships with the percentage of the households that are vacant (0.45, p = 0.00) and the percentage of the households that are rented (0.53, p = 0.00). Both of these relationships are as to be expected, indicating that as the percentage of the population that is in poverty increases, so does the percentage of vacant and rented households in the given location.

The violent crime rate is significantly moderately correlated with the percentage of the population that is unemployed, as well as the percentage of the population that is in poverty. Each of these correlations resulted in coefficients of 0.50 ($p = 0.00$) and 0.44 ($p = 0.00$), respectively. These correlations are as to be expected, indicating that as the population that is unemployed and in poverty increases, so does the violent crime rate. These findings exhibit indicates of high levels of social disorganization in the locations in the study.

The amount of full-time, sworn personnel is significantly moderately correlated with each of the two crime rates, property and violent. The resulting correlation coefficients were 0.41 ($p = 0.00$) and 0.58 ($p = 0.00$), respectively. These relationships are also as to be expected, indicating that more full-time, sworn officers within a police department led to a higher amount of both violent and property crime arrests in a given location.

The population density statistics were also moderately correlated with the percentage of rented households (0.43, $p = 0.00$). This relationship is as to be expected, indicating that as the population density rises, more residences are rented.

Another significant moderate relationship amongst the data was between the median house value and the population in poverty. This relationship showed an expected correlation coefficient of -0.43 ($p = 0.00$), indicating that as the median house value rises, the percentage of the population in poverty goes down.

The median age of the populations of the locations in this study was significantly moderately correlated with two other variables in this study: the percentage of rented households and the percentage of the population in poverty. Both of these relationships resulted in correlation coefficients of -0.54 ($p = 0.00$). These relationships indicated that as the median age goes up in a location, the percentage of rented households and the percentage of the population in poverty go down.

Of all 44 statistically significant correlations between the variables in the study, there were only two that were designated as strong according to Salkind (2011), possessing a correlation coefficient between +/- 0.6 and +/- 0.8.

The first significantly strong correlation was between the percentage of the population in poverty and the percentage of the population unemployed. This relationship resulted in an expected positive correlation coefficient of 0.61 ($p = 0.00$), indicating that as the percentage of the population in poverty rises, so does the percentage of the population that is unemployed.

The second significantly strong correlation was between both of the crime rates, violent and property. The two crime rates have a correlation coefficient of 0.64 ($p = 0.00$), which is to be expected.

Issues Regarding Multicollinearity

As previously mentioned, the main proponent of conducting correlation analyses is to allow for the identification of high relationships between variables in this study. When these correlation analyses were conducted for this study, there was an issue regarding multicollinearity with regards to the “Percentage of the Population in Poverty” variable that was a part of the variables to analyze a location’s social disorganization levels. Secondary tests were conducted through SPSS to analyze the Variance Inflation Factors (VIFs) regarding the independent, social disorganization, and control variables against each of the three dependent variables. VIFs that are high are considered to be above the value of 4.0 and have a tolerance value greater than 0.20 (Goodson & Bouffard, 2017). When these secondary analyses were conducted to evaluate the variables for multicollinearity, the “Percentage of the Population in Poverty” statistic continuously was high in terms of its VIF score, consistently 5.383 across all three dependent variables. This VIF score, as well as its tolerance of 0.186 (below the 0.20 threshold), indicate that this variable is high in terms of multicollinearity. Due to these high indicators of multicollinearity, as well as still having the "Percentage of the Population Unemployed" statistic present to represent the socioeconomic status aspect of the social disorganization framework, it was decided to remove the "Percentage of the Population in Poverty" variable from the models. Further analysis, as well as complete results tables of VIF and tolerance values for all three dependent variables, can be found in Appendix B.

Backwards Stepwise Regression Results

The three research questions seek to find whether or not social disorganization variables have any influence on a police department's use of policing practices such as community policing, crime analysis, and modern technology. Using the three indexes that were created to represent these three policing practices, Backwards Stepwise Regression analysis was conducted in order to find which variables had the most significant impact on predicting the use of community policing, crime analysis, and modern technology amongst the police departments in the sample population.

Backwards Stepwise Regression is a variant of normal multiple regression analysis that involves using predictor variables to explain the variance in a dependent variable (Christensen, 2016). However, instead of simply placing predictor variables into the model to see how well it explains the dependent variable, Backwards Stepwise Regression analysis places all of the predictor variables into a model and then removes variables one by one based upon the significance value of a t-test, which is then compared to a removal criterion. If a predictor meets the removal criterion, it is removed from the model and the model is re-estimated for the remaining predictor variables (Field, 2009, p. 213). This process will continue until there are no more independent variables in the model that meet the removal criterion. As a result, the last model of a Backwards Stepwise Regression analysis will show the most relevant and statistically significant predictor variable(s) that best explain the dependent variable.

As each step progressed, the independent variable that resulted in the smallest R^2 Change was eliminated until the final model was presented. The final models for each of the three dependent variables include the regression results for the most relevant variables used to explain the variance in the dependent variable.

The Backwards Stepwise Regression analysis was conducted using SPSS, with the default parameters set for this analysis. These default parameters include using significance values instead of F values for entry and removal criterion, as well as setting the entry level of .05 and the removal criterion level at .10.

The Backwards Stepwise Regression analysis calculates five very important values to take into consideration: B, Beta, R, R^2, and the Adjusted R^2. The B value, also referred to as the unstandardized coefficient, represents the amount of movement and direction of movement in the dependent variable that would result from the increase or decrease in the independent variable by one unit (Field, 2009). However, since there is a lack of standardization in the B value, it is not highly informative. In turn, the Beta value represents the standardized beta coefficient, or the direction and amount of change in the dependent variable that would result from the increase or decrease of the independent variable by one standard deviation (Field, 2009). The R value is the correlation coefficient between the observed dependent variable value and the predicted value of the independent variable (Salkind, 2011). Having an R value of 1 represents a linear relationship that is a perfectly straight line, while having an R value of 0 represents data that has absolutely no linear relationship. The R^2 value represents the proportion of the variance in the dependent variable that is explained by the independent variable(s). For example, if a regression model were to result in an R^2 value of 0.51, then that means that the model accounts for 51% of the overall variance in the dependent variable. Finally, the adjusted R^2 value represents an estimate of how well the current model would fit into a subsequent model.

Research Question 1: Community Policing

The main objective of the first model was to answer the first research question and evaluate the predictive nature of social disorganization variables on a police department's use of community policing practices. Table 5 provides an overall analysis of the Backwards Stepwise Regression for the community policing dependent variable and is followed by Tables 6, 7, and 8 that break down each of the models individually to express the change in each of the models before and after variables have been eliminated from the model.

Table 5

Community Policing Index Backwards Stepwise Regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.227[a]	0.052	0.028	2.10790	0.052	2.184	10	401	0.018
2	.227[b]	0.052	0.030	2.10530	0.000	0.010	1	401	0.921
3	.227[c]	0.051	0.033	2.10290	0.000	0.081	1	402	0.776
4	.226[d]	0.051	0.035	2.10059	0.000	0.112	1	403	0.738
5	.225[e]	0.051	0.036	2.09872	-0.001	0.279	1	404	0.598
6	.224[f]	0.050	0.038	2.09673	-0.001	0.233	1	405	0.630
7	.221[g]	0.049	0.040	2.09528	-0.001	0.437	1	406	0.509
8	.215[h]	0.046	0.039	2.09562	-0.003	1.134	1	407	0.287

Table 6

Community Policing Backwards Stepwise Multivariate Regression Analysis Models 1, 2, 3

	Model 1			Model 2			Model 3		
	B	Std. Error	Beta	B	Std. Error	Beta	B	Std. Error	Beta
Constant	4.925	1.410		4.914	1.403		5.201	0.976	
Full-Time, Sworn Personnel	0.006	0.003	0.124	0.006	0.003	0.123	0.006	0.003	0.122
Population Density	-8.097E-05	0.000	-0.162	-8.116E-05	0.000	-0.162	-7.823E-05	0.000	-0.156
Median House Value	8.420E-07	0.000	0.064	8.261E-07	0.000	0.062	9.024E-07	0.000	0.068
Percentage of Vacant Housing Units	-0.015	0.019	-0.046	-0.015	0.019	-0.046	-0.015	0.019	-0.046
Violent Crime Rate	-0.003	0.006	-0.039	-0.003	0.006	-0.040	-0.003	0.006	-0.039
Property Crime Rate	0.001	0.001	0.038	0.001	0.001	0.039	0.001	0.001	0.038
Median Age	0.018	0.031	0.039	0.018	0.030	0.040	0.013	0.024	0.028
Percentage of the Population Unemployed	-0.014	0.048	-0.023	-0.017	0.042	-0.026	-0.014	0.041	-0.022
Percentage of Rented Housing Units	0.004	0.014	0.020	0.004	0.014	0.020			
Percentage of the Population Non-white	-0.001	0.008	-0.006						
R		0.227			0.227			0.227	
R^2		0.052			0.052			0.051	
Adjusted R^2		0.028			0.03			0.033	
Std. Error of the Estimate		2.1079			2.1053			2.1029	
R^2 Change		0.052			0			0	
F Change		2.184			0.01			0.081	
df1		10			1			1	
df2		401			401			402	
Sig F. Change		0.018			0.921			0.776	

Table 7

Community Policing Backwards Stepwise Multivariate Regression Analysis Models 4, 5, 6

	Model 4			Model 5			Model 6		
	B	Std. Error	Beta	B	Std. Error	Beta	B	Std. Error	Beta
Constant	5.096	0.923		5.523	0.446		5.557	0.440	
Full-Time, Sworn Personnel	0.006	0.003	0.125	0.006	0.003	0.128	0.007	0.003	0.142
Population Density	-7.995E-05	0.000	-0.160	-8.170E-05	0.000	-0.163	-8.487E-05	0.000	-0.170
Median House Value	9.348E-07	0.000	0.071	1.025E-06	0.000	0.077	9.991E-07	0.000	0.076
Percentage of Vacant Housing Units	-0.018	0.018	-0.054	-0.015	0.017	-0.046	-0.016	0.017	-0.049
Violent Crime Rate	-0.004	0.005	-0.050	-0.004	0.005	-0.054	-0.003	0.004	-0.037
Property Crime Rate	0.001	0.001	0.040	0.001	0.001	0.035			
Median Age	0.013	0.024	0.028						
Percentage of the Population Unemployed									
Percentage of Rented Housing Units									
Percentage of the Population Non-white									
R		0.226			0.225			0.224	
R^2		0.051			0.051			0.05	
Adjusted R^2		0.035			0.036			0.038	
Std. Error of the Estimate		2.10059			2.09872			2.09673	
R^2 Change		0			-0.001			-0.001	
F Change		0.112			0.279			0.233	
df1		1			1			1	
df2		403			404			405	
Sig F. Change		0.738			0.598			0.63	

Table 8

Community Policing Backwards Stepwise Multivariate Regression Analysis Models 7, 8

	Model 7			Model 8		
	B	Std. Error	Beta	B	Std. Error	Beta
Constant	5.563	0.440		5.316	0.374	
Full-Time, Sworn Personnel	0.006	0.002	0.126	0.006	0.002	0.127
Population Density	-8.628E-05	0.000	-0.173	-8.559E-05	0.000	-0.171
Median House Value	1.106E-06	0.000	0.084	1.330E-06	0.000	0.101
Percentage of Vacant Housing Units	-0.018	0.017	-0.054			
Violent Crime Rate						
Property Crime Rate						
Median Age						
Percentage of the Population Unemployed						
Percentage of Rented Housing Units						
Percentage of the Population Non-white						
R		0.221			0.215	
R Square		0.049			0.046	
Adjusted R Square		0.04			0.039	
Std. Error of the Estimate		2.09528			2.09562	
R Square Change		-0.001			-0.003	
F Change		0.437			1.134	
df1		1			1	
df2		406			407	
Sig F. Change		0.509			0.287	

Model 1 utilized the community policing index as the dependent variable and included all independent variables (Percent Non-White, Percentage of Rented Households, Percentage of Vacant Households, Percentage of the Population Unemployed, Median Age, Median House Value, Population Density, Property Crime Rate, Violent Crime Rate, and Full-Time Sworn Personnel[7]). This model resulted in an R value of .227, exhibiting a weak linear relationship between the model and the community policing index variable. An R^2 value of .052 means that this model explained 5.2% of the variance in community policing with all independent variables included. The first variable to be dropped was the %Non-White variable, followed by %Rented, %Unemployed, MedAge, PCR, and VCR, in that order.

The last independent variable to drop is the %Vacant variable, resulting in the final model (Model 8). Dropping this variable lowers the R value to .215, as well as lowers the R^2 value to .046. The final model accounts for 4.6% of the variance in the community policing index variable.

Although the R and R^2 values get weaker throughout the procession of the models, it can be justified through the increased significance levels of the independent variables that make up the final regression model. The FTSworn variable, as well as the PopDen variable, stayed significant throughout the entire Backwards Stepwise Regression process; however, their significance values strengthened from Model 1 to Model 8. For the FTSworn variable, the significance value went from .048 in Model 1 to .009 in Model 8. Also, the PopDen variable went from a significance level of .005 in Model 1 to a significance level of .001 in Model 8. The final regression model shows that these two variables have Beta values of .127 and -.171,

[7] "Percentage of the Population in Poverty" was dropped after the correlation analysis due to multicollinearity issues.

respectively. This means that as there is an increase in the FTSworn variable by one standard deviation, there is an expected rise in the community policing index by .127 of a standard deviation. This also means that as there is a decrease in the PopDen variable by one standard deviation, there is an expected rise in the community policing index by .171 of a standard deviation.

Unlike the FTSworn and PopDen variables, the MHV variable was not always statistically significant throughout the Backwards Stepwise Regression process. MHV started at a significance value of .299 in Model 1, deeming it an insignificant independent variable at the time. Although its significance level steadily increased throughout the models, there was still a lack of statistical significance, until Model 8. In Model 8, after %Vacant was dropped from the regression model, the MHV significance level went from .113 to .046, making it statistically significant for the first time.

Although the final model consists of three statistically significant variables used to explain 4.6%of the variance in the community policing index, neither of these two variables is a part of the list of variables implemented to represent social disorganization levels. Due to this finding, the null hypothesis will be accepted for Research Question 1, concluding that there is no statistically significant relationship between social disorganization variables and the amount of community policing practices in the sample population.

Research Question 2: Crime Analysis

The goal for the second research question was to analyze whether or not police departments in the sample population took into account social disorganization factors of their jurisdiction when it came to implementing crime analysis in their department. Crime analysis was operationalized using an index variable with weighted measures for four separate types of crime analyst employment. These weights were calculated to place a higher emphasis on position types that would exhibit a higher investment in crime analysis on behalf of the department. The overall Backwards Stepwise Regression model is shown in Table 9, followed by tables 10, 11, and 12 that breakdown each of the nine models, in an effort to show the change between the models due to the dropped variables throughout.

Table 9

Crime Analysis Index Backwards Regression Model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.176[a]	0.031	0.007	8.19579	0.031	1.282	10	401	0.239
2	.176[b]	0.031	0.009	8.18564	0	0.005	1	401	0.946
3	.176[c]	0.031	0.012	8.17561	0	0.013	1	402	0.909
4	.176[d]	0.031	0.014	8.16588	0	0.039	1	403	0.844
5	.174[e]	0.03	0.016	8.15744	0	0.163	1	404	0.687
6	.173[f]	0.03	0.018	8.14971	-0.001	0.231	1	405	0.631
7	.164[g]	0.027	0.017	8.15213	-0.003	1.242	1	406	0.266
8	.155[h]	0.024	0.017	8.15465	-0.003	1.252	1	407	0.264
9	.145[i]	0.021	0.016	8.15651	-0.003	1.187	1	408	0.277

Table 10

Crime Analysis Backwards Stepwise Multivariate Regression Analysis Models 1, 2, 3

	Model 1			Model 2			Model 3		
	B	Std. Error	Beta	B	Std. Error	Beta	B	Std. Error	Beta
Constant	2.707	5.483		2.742	5.452		2.630	5.357	
Median House Value	5.546E-06	0.000	0.109	5.594E-06	0.000	0.110	5.639E-06	0.000	0.111
Violent Crime Rate	0.045	0.024	0.146	0.045	0.024	0.146	0.045	0.024	0.147
Percentage of Rented Housing Units	-0.036	0.054	-0.049	-0.036	0.054	-0.049	-0.034	0.050	-0.046
Percentage of the Population Non-White	0.044	0.029	0.096	0.044	0.029	0.096	0.044	0.029	0.097
Percentage of the Population Unemployed	-0.218	0.186	-0.090	-0.222	0.177	-0.092	-0.222	0.176	-0.092
Median Age	0.052	0.120	0.030	0.051	0.117	0.029	0.052	0.116	0.030
Full-Time, Sworn Personnel	-0.003	0.012	-0.018	-0.003	0.012	-0.018	-0.003	0.012	-0.017
Property Crime Rate	-0.001	0.004	-0.013	-0.001	0.004	-0.013	-0.001	0.004	-0.015
Population Density	1.190E-05	0.000	0.006	1.271E-05	0.000	0.007			
Percentage of Vacant Housing Units	-0.005	0.076	-0.004						
R		0.176			0.176			0.176	
R Square		0.031			0.031			0.031	
Adjusted R Square		0.007			0.009			0.012	
Std. Error of the Estimate		8.19579			8.18564			8.17561	
R Square Change		0.031			0			0	
F Change		1.282			0.005			0.013	
df1		10			1			1	
df2		401			401			402	
Sig F. Change		0.239			0.946			0.909	

Table 11

Crime Analysis Backwards Stepwise Multivariate Regression Analysis Models 4, 5, 6

	Model 4			Model 5			Model 6		
	B	Std. Error	Beta	B	Std. Error	Beta	B	Std. Error	Beta
Constant	2.404	5.226		1.868	5.049		4.120	1.877	
Median House Value	5.652E-06	0.000	0.111	5.541E-06	0.000	0.109	6.121E-06	0.000	0.120
Violent Crime Rate	0.043	0.020	0.139	0.039	0.018	0.127	0.038	0.018	0.122
Percentage of Rented Housing Units	-0.033	0.050	-0.045	-0.032	0.050	-0.044	-0.047	0.040	-0.063
Percentage of the Population Non-White	0.045	0.029	0.099	0.045	0.029	0.098	0.043	0.028	0.094
Percentage of the Population Unemployed	-0.222	0.176	-0.092	-0.209	0.173	-0.086	-0.184	0.165	-0.076
Median Age	0.056	0.115	0.032	0.055	0.114	0.031			
Full-Time, Sworn Personnel	-0.004	0.011	-0.022						
Property Crime Rate									
Population Density									
Percentage of Vacant Housing Units									
R		0.176			0.174			0.173	
R Square		0.031			0.03			0.03	
Adjusted R Square		0.014			0.016			0.018	
Std. Error of the Estimate		8.16588			8.15744			8.14971	
R Square Change		0			0			-0.001	
F Change		0.039			0.163			0.231	
df1		1			1			1	
df2		403			404			405	
Sig F. Change		0.844			0.687			0.631	

Table 12

Crime Analysis Backwards Stepwise Multivariate Regression Analysis Models 7, 8, 9

	Model 7			Model 8			Model 9		
	B	Std. Error	Beta	B	Std. Error	Beta	B	Std. Error	Beta
Constant	2.978	1.573		3.241	1.556		1.903	0.955	
Median House Value	7.072E-06	0.000	0.139	7.196E-06	0.000	0.141	6.542E-06	0.000	0.129
Violent Crime Rate	0.031	0.017	0.101	0.036	0.016	0.117	0.032	0.016	0.102
Percentage of Rented Housing Units	-0.052	0.039	-0.070	-0.042	0.038	-0.056			
Percentage of the Population Non-White	0.027	0.024	0.059						
Percentage of the Population Unemployed									
Median Age									
Full-Time, Sworn Personnel									
Property Crime Rate									
Population Density									
Percentage of Vacant Housing Units									
R		0.164			0.155			0.145	
R Square		0.027			0.024			0.021	
Adjusted R Square		0.017			0.017			0.016	
Std. Error of the Estimate		8.15213			8.15465			8.15651	
R Square Change		-0.003			-0.003			-0.003	
F Change		1.242			1.252			1.187	
df1		1			1			1	
df2		406			407			408	
Sig F. Change		0.266			0.264			0.277	

The Backwards Stepwise Regression starts with Model 1, resulting in an R value of .176 and an R^2 value of .031. This means that the initial regression model accounts for only 2.1% of the variance in the crime analysis index variable. The first independent variable to be dropped out of the model is the %Vacant variable. Dropping this variable results in Model 2 having the same R and R^2 values as Model 1, .221 and .031, respectively. Following the %Vacant variable, the PopDen variable is dropped, followed by PCR, FTSworn, MedAge, %Unemployed, and %Non-White, in that order.

After dropping the final variable, %Rented, the final model has an R value of .145 and a final R^2 value of .021. This means that with a final model consisting of the MHV and VCR variables, the model is able to account for 2.1% of the variance in the crime analysis dependent variable.

Once again, the R and R^2 values get weaker throughout the progression of the Backwards Stepwise Regression analysis; however, this weakening of the model can be justified due to the strengthening of the statistical significance of each of the independent variables that make up the final regression model. Unlike in the regression for the first research question pertaining to the community policing index, neither of the two final independent variables started off statistically significant in Model 1. The two final independent variables, VCR and MHV, initially had significance values of .056 and .079, respectively, in Model 1. These two variables also lacked significance in Model 2, when VCR had a significance value of .056 and MHV had a significance value of .069, as well as in Model 3 when VCR had a significance value of .054 and MHV had a significance value of .064. Finally, in Model 4, the VCR variable reached statistical significance with a significance value of .035; however, the MHV variable still lacked statistical significance until Model 6 when it reached a significance value of .027. This progression to statistical significance on behalf of the “Median House Value” variable occurred only after dropping the “Median Age” variable from the regression model.

From the time that the “Median House Value” variable reached statistical significance at Model 6, it never lacked statistical significance. In the final model, the MHV variable had a significance value of .011, eventually stronger in terms of significance than the “Violent Crime Rate” variable.

On the other hand, between Model 6 and Model 7, the VCR variable loses significance, going from a significance value of .033 in Model 6 to a significance value of .062 in Model 7. This lack of significance resulted due to the elimination of the “Percentage of the Population Unemployed” variable; however, in Model 8, after the elimination of the “Percentage of the Population Non-White” variable, the “Violent Crime Rate” variable returns back to statistical significance with a significance value of .025. The “Violent Crime Rate” variable stays statistically significant in the final model with a significance value of .042.

The final regression model shows that the two final variables, “Violent Crime Rate” and “Median House Value, ” both have statistically significant effects on the final model that accounts for 2.1%of the variance in the crime analysis index. The “Violent Crime Rate” variable has a beta value of .102 and the “Median House Value” variable has a beta value of .129, both exhibiting positive correlations with the crime analysis index variable. These beta values mean that if the VCR and MHV variables are increased by one standard deviation, then the crime analysis index will increase by .102 and .129, respectively.

In terms of addressing Research Question 2, the null hypothesis will once again be accepted, concluding that there is no statistically significant relationship between social disorganization levels and a police department’s utilization of crime analysis practices. This conclusion is drawn due to the fact that there is no presence of social disorganization variables in the final model of the regression analysis. Although we do have two statistically significant variables in the final model, “Violent Crime Rate” and “Median House Value, ” neither of these was a part of the social disorganization variables that were placed into the initial model.

Research Question 3: Modern Technology

Research Question 3 was formulated to examine the predictive nature of social disorganization variables on a police department’s use of modern technologies. There were six separate modern technologies that were selected from the 2012 LEMAS database that were included in the modern technology index variable. Table 13 shows the results of the overall Backwards Stepwise Regression process, showing the changes in the model, as independent variables were deemed necessary for removal. Tables 14 and 15 break down each of the six models individually, showing an evaluation of the significance values of each of the independent variables included in each of the six models.

Table 13

Modern Technology Backwards Stepwise Regression Model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.262[a]	0.069	0.045	1.06394	0.069	2.954	10	401	0.001
2	.262[b]	0.069	0.048	1.06267	0.000	0.040	1	401	0.841
3	.261[c]	0.068	0.050	1.06161	0.000	0.199	1	402	0.656
4	.259[d]	0.067	0.051	1.06084	-0.001	0.411	1	403	0.522
5	.257[e]	0.066	0.052	1.06001	-0.001	0.373	1	404	0.542
6	.252[f]	0.064	0.052	1.06013	-0.003	1.087	1	405	0.298

Table 14

Modern Technology Backwards Stepwise Multivariate Regression Analysis Models 1, 2, 3

	Model 1			Model 2			Model 3		
	B	Std. Error	Beta	B	Std. Error	Beta	B	Std. Error	Beta
Constant	4.042	0.712		4.016	0.698		4.052	0.693	
Percentage of the Population Unemployed	-0.047	0.024	-0.146	-0.046	0.024	-0.145	-0.050	0.023	-0.156
Full-Time, Sworn Personnel	0.004	0.002	0.173	0.004	0.002	0.175	0.004	0.002	0.171
Median Age	-0.037	0.016	-0.161	-0.037	0.015	-0.159	-0.037	0.015	-0.158
Percentage of Vacant Housing Units	0.025	0.010	0.145	0.024	0.010	0.144	0.024	0.010	0.026
Percentage of Rented Housing Units	-0.014	0.007	-0.145	-0.014	0.007	-0.140	-0.014	0.006	-0.142
Property Crime Rate	0.000	0.001	-0.041	0.000	0.001	-0.044	0.000	0.000	-0.061
Percentage of the Population Non-White	0.003	0.004	0.047	0.003	0.004	0.047	0.003	0.004	0.045
Median House Value	-2.807E-07	0.000	-0.042	-2.724E-07	0.000	-0.040	-2.596E-07	0.000	-0.039
Violent Crime Rate	-0.001	0.003	-0.034	-0.001	0.003	-0.033			
Population Density	2.926E-06	0.000	0.011						
R		0.262			0.262			0.261	
R Square		0.069			0.069			0.068	
Adjusted R Square		0.045			0.048			0.05	
Std. Error of the Estimate		1.06394			1.06267			1.06161	
R Square Change		0.069			0			0	
F Change		2.954			0.04			0.199	
df1		10			1			1	
df2		401			401			402	
Sig F. Change		0.001			0.841			0.656	

Table 15

Modern Technology Backwards Stepwise Multivariate Regression Analysis Models 4, 5, 6

	Model 4			Model 5			Model 6		
	B	Std. Error	Beta	B	Std. Error	Beta	B	Std. Error	Beta
Constant	4.164	0.670		4.170	0.669		4.026	0.655	
Percentage of the Population Unemployed	-0.046	0.022	-0.142	-0.039	0.019	-0.121	-0.042	0.018	-0.133
Full-Time, Sworn Personnel	0.004	0.002	0.168	0.004	0.002	0.174	0.004	0.001	0.137
Median Age	-0.041	0.014	-0.176	-0.042	0.014	-0.179	-0.038	0.013	-0.162
Percentage of Vacant Housing Units	0.009	0.153	0.099	0.026	0.009	0.152	0.026	0.009	0.152
Percentage of Rented Housing Units	-0.016	0.006	-0.159	-0.015	0.006	-0.154	-0.014	0.006	-0.145
Property Crime Rate	0.000	0.000	-0.058	-0.001	0.000	-0.065			
Percentage of the Population Non-White	0.002	0.004	0.037						
Median House Value									
Violent Crime Rate									
Population Density									
R		0.259			0.257			0.252	
R Square		0.067			0.066			0.064	
Adjusted R Square		0.051			0.052			0.052	
Std. Error of the Estimate		1.06084			1.06001			1.06013	
R Square Change		-0.001			-0.001			-0.003	
F Change		0.411			0.373			1.087	
df1		1			1			1	
df2		403			404			405	
Sig F. Change		0.522			0.542			0.298	

The initial regression model used to explain the variance in the modern technology index variable includes all 10 of the independent variables, resulting in an initial R value of .262 and an initial R^2 value of .069. This means that the initial model accounts for 6.9% of the variance in the modern technology dependent variable when all independent variables are included in the model. The first independent variable to be eliminated in the "Population Density" variable, resulting in Model 2 having no change from Model 1 with an R value of .262 and an R^2 value of .069. We still are only able to account for 6.9% of the variance after dropping the "Population Density" variable. Model 3 sees the elimination of the VCR variable, followed by MHV, %Non-White, and PCR, in that order.

The final model, Model 6, includes five variables: "Percentage of the Population Unemployed," "Full-time Sworn Personnel," "Median Age," "Percentage of Vacant Households," and "Percentage of Rented Households." This final model has an R value of .252 and an R^2 value of .064. The final model, which includes five independent variables, accounts for 6.4% of the variance in the modern technology dependent variable.

Although there was a consistently small drop in the amount of variance that the regression models explained throughout the Backwards Stepwise Regression process, this drop in the R^2 value can be justified through the improvement of significance on behalf of the independent variables in the final model. With the exception of the %Unemployed variable, all of the independent variables in the final model were statistically significant within the model from the onset of the regression process. FTSworn started off significant at .005 in Model 1, however, gained significance throughout the regression process to finish with a statistical significance value of .004. MHV, %Rented, and %Vacant saw improvements in their significance values as well, dropping from .017 to .005, from .041 to .015, and from .013 to .007, respectively.

The only variable that was a part of the final regression model was the %Unemployed variable. In Model 1, %Unemployed's statistical significance was .055 and stayed at this significance value in Model 2 as well. After dropping the "Violent Crime Rate" variable in Model 3, %Unemployed finally reached statistical significance with a p-value of .029. From Model 3 on, this variable stayed statistically significant and finished with a significance value of .020 in Model 6.

Research Question 3 asked whether or not a police department's utilization of modern technologies could be predicted based upon its social disorganization levels. The hypothesis for this research question predicted a positive relationship between social disorganization levels and use of modern technology. Seeing as there is a positive relationship between the "Percentage of Vacant Households" variable and the modern technology index, we can accept this hypothesis. Although two other social disorganization variables are present in the final model (i.e., "Percentage of Rented Households" and "Percentage of the Population Unemployed"), these relationships are negative in nature, supporting the opposite of what the hypothesis was predicting.

Summary

The overall purpose of this chapter was to outline the findings based on the three statistical analyses that were conducted in the study. Descriptive statistics were first outlined, followed by a Pearson's correlation analysis in order to check for multicollinearity, and concluded with three separate Backwards Stepwise Regression models that were formulated to answer the three research questions that directed this study.

The descriptive statistic results showed that, among the social disorganization variables, the average location had 31.24% of a Non-White population, with 10.44% of the households vacant and 39.33% of them rented. The locations in this study also had an average of 17.59% of their population living in poverty as well as 9.93% of the population unemployed.

In terms of crime rates, the average location had a violent crime rate of 32.9 and a property crime rate of 265.85, with an average full-time, sworn police force of 135.96 officers. The locations in this study also had an average population density of 3,754.06 persons per square mile, with a median house value of 230,927.82 dollars. The average median age of these locations was 35.81 years.

The average values for the community policing, crime analysis, and modern technology indexes were 6.17, 4.49, and 2.44, respectively. This means that the average police department in this study participated in roughly six out of 10 community policing practices, had, on average, 4.5 full-time, sworn crime analysts (or an equal combination of the other three analyst position types), and utilized between two and three of the modern technologies included in the TECH index variable.

The Pearson correlation results highlight some very specific relationships relating to the social disorganization variables as well as the community policing index. First, all five of the social disorganization variables[8] are positively correlated to the violent crime rate. According to Salkind (2011), one of these relationships was very weak ("Percentage of Vacant Households" p = .19) and two of these relationships were weak ("Percentage of the Population Non-White" p = .31, "Percentage of Rented Households" p = .21). However, the "Percentage of the Population

[8] "Percentage of the Population in Poverty," "Percentage of the Population Unemployed," "Percentage of the Population Non-White," "Percentage of Vacant Households," "Percentage of Rented Households"

Unemployed" and "Percentage of the Population in Poverty" variables both had moderate correlation strength with p-values of .50 and .44, respectively. This translates into saying that an increase in all of the social disorganization variables that were implemented in this study relates to an increase in the violent crime rates of their accompanying locations.

Another notable trend in the correlation results shows that the community policing index has statistically significant, positive correlations with each of the other index variables. COP has a correlation coefficient of .109 ($p < .05$) with the crime analysis index as well as a correlation coefficient of .141 ($p < .01$) with the modern technology index.

The first regression model indicates that there were only three variables that were vital in explaining the overall variance in the community policing index: "Full-Time, Sworn Personnel," "Population Density," and "Median House Value." Although the progression of the Backwards Stepwise Regression models showed a decrease in the overall R^2 value, it is justified due to the increase in the significance of these three final independent variables. The final model that includes the final three independent variables has an R^2 value of .046, meaning that the model explained 4.6% of the overall variance in the community policing index.

Model 2 shows that the crime analysis index's variance can be explained using only two independent variables: "Median House Value" and the "Violent Crime Rate." Again, the progression of the models indicates a loss in the explanation of variance in the crime analysis index; however, this loss is justified through the strengthening of the significance of the two independent variables in the final model. The final model that includes the final two independent variables has an R^2 value of .021, meaning that 2.1% of the overall variance in the crime analysis index is explained by the model.

The modern technology index is the dependent variable in the third, and final, regression model. This model shows that the modern technology index's variance can be explained using five independent variables: "Percentage of the Population Unemployed," "Full-Time, Sworn Personnel," "Median Age," "Percentage of Rented Households," and "Percentage of Vacant Households." Most notably, this is the only dependent variable whose final regression model includes any social disorganization variables. This finding will be discussed further in the following chapter. Overall, the final model in this regression process has an R^2 value of .064, accounting for 6.4% of the variance in the modern technology index.

A further discussion of these findings as well as the implications that accompany these findings will be provided in the following chapter. Furthermore, an analysis of the limitations of this study as well as recommendations for future research involving Social Disorganization Theory and its relationship to community policing, crime analysis, and modern technology practices on behalf of police departments will also be proposed.

Chapter 5: Discussion, Implications, Limitations, and Future Research

The overall goal of this research was to determine whether or not the social disorganization levels within a community had a predictive nature regarding its police department's use of community policing, crime analysis, and modern technology. This chapter offers a discussion regarding the results and their implications on policing practices in the United States. This chapter then concludes with the limitations of the study as well as recommendations for future research to help develop a deeper understanding of these policing principles.

Research Question 1: Community Policing

Research Question 1 asked "How does a community's level of social disorganization predict how its police department practices community policing?" The findings did not find that the five social disorganization variables were statistically significant regarding predicting a department's community policing practices. This means that the accompanying hypothesis, predicting that a higher social disorganization level within a community will correspond to an increase in community policing practices, lacks evidence to be supported. Although the final regression model is weak with a significance value of .287, these conclusions are drawn based on the direction of the relationships and their accompanying beta and R^2 values.

Although there is a lack of evidence supporting the research hypothesis, the findings do indicate that there are three control variables that are related to a police department's use of community policing practices, including the amount of full-time, sworn officers, the population density of the jurisdiction, and the median house value of the residences within the jurisdiction. The results show that the departments with more officers, which police less densely populated jurisdictions with higher median house values, participate in more community policing practices, such as including community policing in their department's mission statement, providing community policing training for recruits and sworn staff, and other practices that were included in the COP index. While the specific variables within the COP index were not dissected in the analysis, the descriptive statistics of the individual index variables show that more agencies participated in practices such as assigning the same officers to the same geographic beats or areas (85.4%), including community policing in their mission statement (87.3%), and allowing their citizens to receive information via text message or email (74.6%). Further analysis of these variables on an individual basis within the context of the COP index will allow for better understanding surrounding which of these practices has the most influence on community policing practices.

The findings from this study do not find that police departments in cities with differing levels of social disorganization are utilizing community policing practices differently, as originally hypothesized, but are implementing community policing differently in communities that vary by the density of their population and median house value. Implementation of community policing also varies by department size, in that agencies with more officers, which police in areas with less population density and more affluence, utilize community policing on a more prevalent basis.

These findings do not support the theoretical framework of Social Disorganization Theory proposed by Shaw and McKay (1942). Shaw and McKay (1942) stated that the areas in the inner regions of the city will have higher crime rates due to low socioeconomic status, high ethnic/racial heterogeneity, and the highly transient nature of their population. However, the presence of these three final independent variables shows that police departments are more likely to practice community policing in areas that are more affluent (as the median house value rises), less crowded (as the population density decreases), and have more officers (being able to afford to pay them).

Research Question 2: Crime Analysis

Research Question 2 asked "How does the community's level of social disorganization predict whether the police department has a crime analysis function?" Once again, the findings fail to indicate that social disorganization is statistically related to crime analysis within a jurisdiction. Based upon these findings, there is a lack of support of the original research hypothesis, predicting a positive relationship between social disorganization levels and crime analysis. In turn, the null hypothesis, claiming a lack of a relationship, is accepted. Although the final regression model is weak with a significance value of .277, these conclusions are drawn based on the direction of the relationships and their accompanying beta and R^2 values.

There are two control variables related to a department's use of crime analysis: the violent crime rate and the median house value. These findings suggest that departments invest in crime analysis when they have more violent crime and a higher median house value regardless of their community's social disorganization level.

The median house value represents increased financial affluence of the community. As the median house value increases, the means necessary to reside in these communities rise as well, attracting a more affluent population compared to a community with a lower median house value. The median house value variable being a part of the final regression model indicates that the more affluent areas of the sample population of the study are those that are investing more resources in a crime analysis strategy in order to combat a high violent crime rate, simply because their affluent residents have more money to pay taxes towards the police department. Thus, it appears that when departments are faced with increased violent crime rates and have the resources to do so, they invest in more crime analysis personnel, placing a higher level of emphasis on crime analysis on behalf of the department.

Descriptive statistics show that there are more full-time (both sworn and non-sworn) analysts hired in the departments in the sample population in comparison to their part-time counterparts. This may indicate that the departments that have a high crime rate and have the funds are investing not only in a crime analyst, but investing in full-time analysts compared to part-time analysts. This exhibits a higher level of investment in crime analysis strategies, seeing as the hiring of full-time analysts includes a higher salary and benefits package compared to hiring a part-time analyst.

Research Question 3: Modern Technology

Research Question 3 asked "How does a community's level of social disorganization predict how police use advanced technology?" In an overall weak final regression model ($p = .298$), the findings are mixed with regards to social disorganization. There is some evidence to support the hypothesis that police departments serving higher areas of social disorganization use more modern technologies since the percent of vacant households variable is present in the final model. This finding provides menial support for the research hypothesis, predicting that the social disorganization level within a community correlates with its police department's utilization of modern technology. The final regression model shows that the percent of vacant households within a jurisdiction is positively related to the use of modern technology, in that more vacant households present within a community leads to more implementation of modern technologies like GSD systems, LPRs, and various camera surveillance technologies. However, the percent of vacant households variable was not the only independent variable exerting a statistically significant influence on the variation of the modern technology index.

Four independent variables are significantly related to the use of modern technology and three of the four are control variables that represent the financial affluence of the community. The lower percentage of rented households implies that a higher percentage of the population owns their houses, and these departments utilize modern technology at a higher rate. The fact that these communities have a higher percentage of homeowners represents the financial affluence to own a home, portraying a community with higher financial resources.

Another control variable in the final model that represents financial affluence is the percentage of the population that is unemployed. As the percentage of the population that is unemployed goes down, the use of modern technology will rise on behalf of the police department. In turn, these communities have a higher percentage of their population employed, representing a more affluent community. The fact that a higher percentage of the community is employed also translates to higher tax revenue for public service departments, such as the police department.

The final regression model also shows that, as the amount of full-time, sworn personnel within a department increases, the use of modern technology increases. This finding also supports the claim that these communities are affluent, as their tax streams into public service offices like the police department have allowed for them to invest in a larger staff. All of these three previously mentioned findings show that there is more adequate financial support on behalf of the police department, seeing as the population is employed at a higher rate, and has the money to be able to afford their houses as well as provide a higher tax revenue for police departments to be able to afford more police officers.

Furthermore, although not a part of the research hypotheses, it is also expected to see that departments that have a more youthful population (the median age decreases) are investing in modern technologies at a higher rate. Seeing as the age-crime relationship indicates that the majority of all types of crime occur before the age of 30 (Ulmer & Steffensmeier, 2014), this relationship is to be expected. The relationship between the median age of the population and its department's use of modern technology is the strongest out of the independent variables included in the final regression model. This indicates that the median age of the residents in a jurisdiction has the strongest predictability regarding a department's use of innovative technologies.

Discussion Across Models

While all three regression models are weak based upon their significance values (i.e., Model 1 = .287, Model 2 = .277, and Model 3 = .298), the models are best described by their R^2 values, representing the amount of the variation that is accounted for by the final model in the regression. The model that best describes its accompanying dependent variable is the model for the modern technology index (Model 3); however, seeing as this model only accounts for 6.4% of the variation in the modern technology index, it is not a strong model. The modern technology regression also has the most significant variables within the final model (5) and is also the only one to have a social disorganization variable present (percent of vacant households). The fact that the modern technology index has more statistically significant independent variables may indicate that these departments are more financially prepared due to a more affluent jurisdiction, portrayed by low house rental rates, high numbers of sworn officers, and low unemployment rates.

Community policing and crime analysis have the median house value as a similar independent variable across the two models. This might be because it takes an investment on behalf of the community to implement a community policing philosophy as well as a crime analysis department. This similarity also depicts that communities that have police departments that invest in community policing initiatives and crime analysis are more affluent, represented by their increased median house value.

The community policing and modern technology models have the full-time, sworn personnel variable in common. This finding indicates that having more officers within an agency is predictive of the department's implementation of a community policing strategy as well as its utilization of modern technology. This finding might be because of funding within the department, seeing as the department is investing manpower in a community policing initiative as well as financial resources to invest in modern technologies, inferring that departments that police more affluent communities invest in these two policing strategies.

The crime analysis model and the modern technology model have no statistically significant independent variables in common between their two final models. This indicates that police departments do not take into account the same factors when it comes to implementing a crime analysis strategy as it does utilizing modern technologies. Further research could be focused on developing a deeper understanding of the relationship between crime analysis and modern technologies within police departments.

Overall, the main finding of this research implies that these three policing practices (community policing, crime analysis, and modern technology) are being utilized in areas of higher affluence and continuity of residence. This might be because the residents of these communities not only are investing a higher amount of tax dollars into their public service offices, like their police department, but they also are more invested in the social structure of the community, seeing as their residency is extended compared to having a transient population.

Implications

The findings from this research, although they are very weak, do provide practical implications for local police departments with between 75 and 250 sworn personnel. Overall, these three policing practices, community policing, crime analysis, and modern technology, are not being utilized in areas with high levels of social disorganization. This is concluded because of the lack of social disorganization variables in the three models, with the exception of percent of vacant households in the modern technology regression model.

Implications for COP. In a community policing context, police departments that serve less affluent and denser areas need financial assistance and encouragement to participate in community policing-related initiatives, regardless of their social disorganization levels. Community policing philosophies are outlined to help improve relationships between the community and the police department and have been proven to help increase the legitimacy of police departments within their communities (Hawdon, Ryan, & Griffin, 2003). This research indicates that police departments that are more affluent practice community policing (based upon their increased median house values and higher staff numbers), which is not where Social Disorganization Theory asserts that we should direct community policing.

Funds from federal organizations such as the COPS Office within the Department of Justice have continually financed departments to help improve community policing since 1994. Fiscal year 1994 saw an investment of 894 million dollars in COPS hiring grants on behalf of the Department of Justice (United States Department of Justice, Office of Community Oriented Policing Services, 2014c). Over the years, there has been a reduction in the investment of COPS hiring grants, falling to an overall investment of only just over 111 million dollars in 2012 (United States Department of Justice, Office of Community Oriented Policing Services, 2012) and just over 98 million dollars in 2017 (United States Department of Justice, Office of Community Oriented Policing Services, 2017), exhibiting a 90% decrease in overall investment in COPS hiring grants within this span.

Although the overall investment has declined since the initiation of the COPS hiring grants program, there is still an adequate amount of resources being allocated for COPS hiring grants since the initiation of the COPS Office in 1994. Although 98 million dollars seems miniscule when compared to 894 million dollars, COPS hiring grants still awarded funds for the financing of 802 community policing-dedicated officer positions in the 2017 fiscal year (United States Department of Justice, Office of Community Oriented Policing Services, 2017).

Even though there has still been a substantial amount of funding dedicated to hiring community policing-based officers in departments across the country, areas plagued by high levels of social disorganization are still battling high violent and property crime rates, as well as issues regarding police legitimacy. If community policing efforts are focused to areas of high levels of social disorganization, then these efforts will become focused and, in turn, increase the legitimacy of their departments at a higher rate than they already are. Also, focusing the efforts of community policing initiatives will provide this service to the communities that need it due to their issues regarding police legitimacy (Gau, Corsaro, Stewart, & Brunson, 2012), even if funding goes from one department that does not have high disorganization rates to another department that does have high disorganization rates. Reallocation of these funds to departments battling high social disorganization rates can be the first step in addressing policing legitimacy issues in a community policing and social disorganization context.

Implications for CA. Overall, it has been found that crime analysis is not just for crime-prone areas, but to focus crime reduction efforts for more efficiency (Weisburd & Majmundar, 2018), as well as being a vital aspect of police practices focused on reducing crime (Santos, 2014). This research indicates that police departments serving violent communities have placed more of an emphasis on crime analysis, providing a parallel with the aforementioned research.

Implications regarding crime analysis center around providing the areas that have not been found to have high violent crime rates with the awareness and/or funding to implement crime analysis. This expansion will allow these departments that do not have high violent crime rates to see that crime analysis is still essential in a police department with non-violent communities, regardless of the policing initiative it has chosen to implement (Santos, 2014).

Funding initiatives can also be paired with the aforementioned COPS grants from the previous section of this chapter. Seeing that not only does crime analysis effectively allow for policing efforts to be focus and targeted (Weisburd & Majmundar, 2018), but that all forms of policing are effective only through the inclusion of a crime analysis strategy (Santos, 2014), the marriage of these two disciplines will have a proliferated effect on crime rates. This combination of the two principles will also provide the crime analysis discipline with the funding and development that it needs in order to become respected by policing supervisors, addressing two of the most prevalent issues surrounding crime analysis today (Santos, 2017).

Implications for TECH. Overall, it has been found that the use of modern technologies such as GSD systems, LPRs, GIS, Body Worn Cameras, and several different types of camera surveillance technology has been effective in not only helping to identify and reduce crime (Piza et al., 2014; Piza et al., 2016; Shah & Braithwaite, 2013), but in improving relationships between the community and its police department through an increased level of communication (Ariel, 2017; Bertot et al., 2010; Braga et al., 2018; Brainard & Derrick-Mills, 2011; White et al., 2017). The findings of this research indicate that police departments in the sample population are more likely to utilize modern technologies if they are faced with high rates of vacant households, one of the social disorganization variables. This finding supports the research hypothesis; however, the percentage of vacant households statistic is not the most adequate independent variable in terms of predicting a department's use of modern technology.

Other variables in the final regression model for predicting the use of modern technology are percentage of the population unemployed, percent of rented households, median age, and the amount of full-time, sworn personnel[9]. These findings show that police departments that have a larger sworn staff, with a population that is employed at a higher rate, younger, and owns their homes compared to renting them, are more likely to utilize modern technologies.

As with the findings from the previous two regression models, the amount of full-time, sworn personnel indicates a population with higher affluence, seeing as they are able to invest more tax dollars into their police departments. For this model, we can add the percentage of the population unemployed and the percentage of rented household findings to this affluence justification, seeing as this model has negative relationships between these two independent variables and the use of modern technology. In turn, the more people that are employed and the more people who own their homes compared to renting their homes (both signs of affluence amongst the population) leads to the use of modern technology on behalf of the police department.

This finding should be the focus of adjusting the implementation of modern technologies, expanding the use of these technologies to departments that cannot afford them due to a lack of adequate tax revenue from their communities. One way that this could possibly be done is

[9] %Unemployed and %Rented are both SD variables; however, the direction of their relationship with the TECH index does not support the direction of the hypothesis.

through the initiation of joint task forces between departments with adequate financing and those without adequate financing. These joint task forces could then apply for funding through the government, or even combine funding they have within their separate departments, in order to afford these modern technologies. This allows the cost of the technologies to be lowered (for the individual department) and allows departments with less funding to reap the benefits of modern technologies to help identify and lower crime rates, as well as improve citizen-police communication within their jurisdiction.

Overall, community policing, crime analysis, and modern technologies are not being utilized by police departments as they should be in areas with high levels of social disorganization. Proper development of these policing practices in real-world contexts will require the proper financing of these initiatives, to allow for these practices to be expanded to areas battling high levels of social disorganization.

Limitations

There are several limitations of this study. The first is a limitation of the methodology used for LEMAS, stemming from the fact that this studyused self-reported survey data from the LEMAS database. Self-reported data fails to provide any uniformity between respondents, leading to a severe lack in the reliability of the data.

The use of secondary data is the second limitation of the study. All forms of data utilized for the statistical analysis, LEMAS, UCR, and Census data, were all secondary data. Secondary data does not allow researchers to manipulate the data to be specified towards their research questions. Specific manipulation issues pertaining to this study begin with how the percentage of the population unemployed statistic had to be calculated in order to combine both gender's unemployment rates into one statistic. Also, a weighted scores system had to be implemented in order to operationalize the emphasis that a police department places on crime analysis.

The third limitation of this study lies with the use of UCR data. Although this data was only used for control variables in this study (i.e., violent crime rate and property crime rate), the UCR is only a database of reported crimes throughout the country. This report fails to take into account the crimes that go unreported to police departments. Although this is an issue with all studies that utilize UCR data, this is a particular issue for this study because there was not a further breakdown of the crime rates past the general categories provided by the FBI. There was no subsequent breakdown of these items due to the fact that the violent and property crime rates were only utilized for control variables in this study.

Another limitation of this study is with regards to the data utilized for Census data. USA.com is a reliable source for Census data; however, its publications are aggregated into 4-year periods. The aggregation period used for the social disorganization variables was from 2010 to 2014. Although the timetable overlaps with the UCR crimes as well as the 2012 LEMAS database, the inclusion of the other 4 years in this aggregation could misrepresent the social disorganization levels of the cities in this study.

Another limitation of this study is regarding the age of the data used. Data were aggregated and collected for the 2012 fiscal year in an attempt to match the LEMAS database utilized, seeing as it was the most recent release of this database when this research came to fruition. However, this data is now 7 years old at the time of completion of this research. This is an issue, especially regarding the crime analysis and modern technology portions of this research, seeing as these two disciplines are constantly evolving and developing new ways to be introduced into police departments in America on a daily basis.

Furthermore, the unit of analysis being local police departments with sworn personnel between 75 and 250 officers limits the interpretation of this study's findings, particularly with regards to findings related to Social Disorganization Theory. This unit of analysis limits the findings to be applied to large, suburban police departments, most of which do not exhibit the social disorganization issues that Shaw and McKay (1942) first noticed in Chicago.

The final weakness of this study is the fact that only a very weak explanation can be derived from its results. This weak explanation is due to the fact that there is a lack of statistically significant effect on the three dependent variables from the social disorganization variables that were implemented in the study.

Recommendations for Future Research

Seeing as there was not much of a relationship between Social Disorganization Theory and these three policing practices, future research should focus on a deeper understanding of these disciplines separately. A deeper understanding of these practices and theory on a separate level will allow practitioners to potentially combine them in the future for a more adequate policing approach.

This piece of research provides a starting point for future research that could continue to develop the association between Social Disorganization Theory and police practices throughout the country. The initial recommendation for future research is to continue this research framework throughout the continuing releases of LEMAS databases. LEMAS databases are released roughly every four years, with a new database being released from data collected in 2016. This development of a longitudinal study will help researchers not only understand the association of Social Disorganization Theory and policing practices on a deeper level, but how these practices may change throughout time as new policies are implemented throughout the country.

These future research ventures should also focus on the development of the index variables that were utilized as the dependent variables in this study, especially pertaining to the community policing and modern technology indexes. The evaluation of these variables should begin with determining which of the factors from the LEMAS study are most vital to include in these indexes, so as to portray community policing and modern technology in a more adequate fashion. Once these indexes are developed and include the most vital aspects of these two principles, they can be used to provide better insight to researchers, and in turn police departments, about the most adequate way to utilize these practices.

This study focused on police departments that were local departments with between 75 and 250 full-time, sworn police officers. The objective of instituting these parameters of this study population was to capture the suburban police department that had adequate human and financial resources to implement the practices included in the study. However, the original theoretical framework of Social Disorganization Theory proposed by Shaw and McKay (1942) focused on the inner cities (Chicago to be specific). McGuire and colleagues (1997) found that there were different aspects of community policing that were effective in different social settings, so future research should attempt to evaluate inner city police departments as well as suburban police departments. This inclusion of inner city departments will not only allow for a better understanding of the association between Social Disorganization Theory and the three policing practices, but will provide researchers with an understanding of what may work better in urban and rural populations, especially pertaining to community policing efforts. This diversification of the study might also start with defining the parameters based on the population of the cities that are included in the analysis, in an attempt to make the study parallel with the definitions provided by the United States Census Bureau. The Census Bureau defines an “Urban Area” as a location with a population of 50,000 or more citizens. Distinguishing between urban and rural areas will also allow for a cross-sectional evaluation of the differences between urban and rural police departments and their policing practices.

Future research might also include the index variables in the regression analysis that was conducted. Inclusion of these indexes as independent variables will allow researchers to see whether or not any of the indexes are predictive upon another. For example, findings might conclude that the inclusion of more modern technologies increases as community policing increases as well.

Conclusion

Recent years have seen an increase in the implementation of policing practices such as community policing, crime analysis, and modern technologies. These three policing practices have all been shown to not only help police departments identify and combat crime, but also improve the relationships between community members and their departments. Social Disorganization Theory provides an adequate theoretical framework that could be used to identify areas and communities for which these three policing techniques should be implemented, describing areas of low socioeconomic status and high rates of ethnic/racial heterogeneity and residential instability. However, this research finds that Social Disorganization Theory is not a factor when it comes to departments with different levels of social disorganization implementing these practices. Instead, this research indicates that factors such as the amount of full-time, sworn personnel within the department, as well as the violent crime rate, percentage of rented and vacant households, population density, median house value, and median age of the jurisdiction have the ability to predict the level of implementation of community policing, crime analysis, and modern technology.

Policies need to be developed that will allow for those departments that police areas with less affluent populations to be able to afford and, in turn, reap the benefits of these policing practices. Further research will then be able to expand the knowledge of these policing practices, as well as how it associates with the theoretical framework of Social Disorganization Theory.

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Appendix A

Index Component Variables Descriptive Statistics

This appendix is an effort to be completely forthwith regarding all results that are included in this research. Appendix A will exhibit three separate tables, two of them being frequency distribution tables and one being a descriptive statistics table of measures of central tendency. These three tables will show the frequencies and descriptive statistics of all of the variables that comprised the index variables that were used in this study.

The first table will show the frequencies of all of the community policing measurements from the LEMAS database that were used to create the community policing index. The second table will be a descriptive statistics table showing measures of central tendency for the four different types of crime analysis positions that were used to create the crime analysis index variable. The third, and final, table in Appendix A will show the frequency distributions of the six modern technologies that were included in the modern technology index variable.

Table A1

Community Policing Frequency Distribution

		Frequency	Percent	Valid Percent	Cumulative Percent
Sara-Type Problem Solving Projects Actively Encouraged	No	146	34.9	34.9	34.9
	Yes	272	65.1	65.1	100
	Total	418	100	100	
Evaluation Criteria for Patrol Officers Includes Collaborative Problem-Solving Projects	No	214	51.2	51.2	51.2
	Yes	204	48.8	48.8	100
	Total	418	100	100	
Problem-Solving Partnership or Written Agreement with Local Organization	No	175	41.9	41.9	41.9
	Yes	243	58.1	58.1	100
	Total	418	100	100	
Same Patrol Officers Regularly Assigned Responsibility for Areas or Beats	No	61	14.6	14.6	14.6
	Yes	357	85.4	85.4	100
	Total	418	100	100	
Utilized Information from a Community Survey	No	227	54.3	54.3	54.3
	Yes	191	45.7	45.7	100
	Total	418	100	100	
Public Can Report Crimes by Email or Texting	No	197	47.1	47.1	47.1
	Yes	221	52.9	52.9	100
	Total	418	100	100	
Public Can Receive Information through Email or Texting	No	106	25.4	25.4	25.4
	Yes	312	74.6	74.6	100
	Total	418	100	100	
Mission Statement has a Community Policing Aspect	No	53	12.7	12.7	12.7
	Yes	365	87.3	87.3	100
	Total	418	100	100	
All Recruits have 8+ hours of Community Policing training	No	172	41.1	41.1	41.1
	Yes	246	58.9	58.9	100
	Total	418	100	100	
Half of Recruits have 8+ hours of Community Policing Training	No	412	98.6	98.6	98.6
	Yes	6	1.4	1.4	100
	Total	418	100	100	
All Personnel have 8+ hours of In-Service Community Policing Training	No	303	72.5	72.5	72.5
	Yes	115	27.5	27.5	100
	Total	418	100	100	
Half of Personnel have 8+ hours of Community Policing Training	No	371	88.8	88.8	88.8
	Yes	47	11.2	11.2	100
	Total	418	100	100	

Table A2

Crime Analysis Positions Descriptive Statistics

	Minimum	**Maximum**	**Mean**	**Std. Deviation**	**Variance**	**Skewness**		**Kurtosis**	
						Statistic	**Std. Error**	**Statistic**	**Std. Error**
Full-Time, Sworn Personnel	0	54	2.13	5.211	27.153	4.867	0.127	32.884	0.254
Full-Time, Non-Sworn Personnel	0	109	2.12	10.897	118.740	7.938	0.125	68.649	0.250
Part-Time, Sworn Personnel	0	33	1.69	3.033	9.200	5.661	0.126	42.123	0.251
Part-Time, Non-Sworn Personnel	0	8	0.40	0.994	0.987	3.578	0.125	16.342	0.250

Table A3

Modern Technology Frequency Distribution

		Frequency	Percent	Valid Percent	Cumulative Percent
Utilized Gun Shot Detection Systems	No	377	90.2	90.2	90.2
	Yes	41	9.8	9.8	100
	Total	418	100	100	
Utilized License Plate Readers	No	167	40	40	40
	Yes	251	60	60	100
	Total	418	100	100	
Utilized Video Surveillance of Public Areas	No	112	26.8	26.8	26.8
	Yes	306	73.2	73.2	100
	Total	418	100	100	
Utilized Video Surveillance in Patrol Vehicles	No	132	31.6	31.6	31.6
	Yes	286	68.4	68.4	100
	Total	418	100	100	
Utilized Video Surveillance on Patrol Officers	No	324	77.5	77.5	77.5
	Yes	94	22.5	22.5	100
	Total	418	100	100	
Utilized Video Surveillance on Weapons	No	375	89.7	89.7	89.7
	Yes	43	10.3	10.3	100
	Total	418	100	100	

Appendix B

VIF Scores for Variable: Percentage of the Population in Poverty

Through the conduction of a correlation analysis, it was found that there were high correlations between the variable "Percentage of the Population in Poverty" and other variables associated with the measures of levels of social disorganization within a community, the percentage of the households that were rented, and the percentage of the population that was unemployed. Once these initial flags were raised through the correlation results, an analysis of Variance Inflation Factors (VIFs) was then conducted using SPSS. The results of these three analyses (one for each dependent variable) are shown in the following tables. Due to the high VIFs revolving around the Percentage of the Population in Poverty statistic, it was decided to remove it in order to avoid issues regarding multicollinearity.

Table B1

VIF Levels: Community Policing Index

	Collinearity Statistics	
Model[a]	**Tolerance**	**VIF**
Property Crime Rate	0.411	2.436
Violent Crime Rate	0.412	2.430
Full-Time, Sworn Personnel	0.591	1.691
Population Density	0.688	1.453
Median Age	0.409	2.446
Median House Value	0.551	1.816
Percentage of Population Non-White	0.593	1.686
Percentage of Rented Housing Units	0.333	3.004
Percentage of Vacant Housing Units	0.502	1.991
Percentage of Population Unemployed	0.341	2.929
Population in Poverty	0.186	5.383

a. Dependent Variable: COP Index

Table B2

VIF Levels: Crime Analysis Index

	Collinearity Statistics	
Model[a]	**Tolerance**	**VIF**
Property Crime Rate	0.411	2.436
Violent Crime Rate	0.412	2.430
Number of Full-time, Sworn Personnel	0.591	1.691
Population Density	0.688	1.453
Median Age	0.409	2.446
Median House Value	0.551	1.816
Percentage of Population Non-White	0.593	1.686
Percentage of Rented Housing Units	0.333	3.004
Percentage of Vacant Housing Units	0.502	1.991
Percentage of Population Unemployed	0.341	2.929
Population in Poverty	0.186	5.383

a. Dependent Variable: Crime Analysis Index

Table B3

VIF Levels: Modern Technology Index

	Collinearity Statistics	
Model[a]	**Tolerance**	**VIF**
Property Crime Rate	0.411	2.436
Violent Crime Rate	0.412	2.430
Number of Full-time, Sworn Personnel	0.591	1.691
Population Density	0.688	1.453
Median Age	0.409	2.446
Median House Value	0.551	1.816
Percentage of Population Non-White	0.593	1.686
Percentage of Rented Housing Units	0.333	3.004
Percentage of Vacant Housing Units	0.502	1.991
Percentage of Population Unemployed	0.341	2.929
Population in Poverty	0.186	5.383

a. Dependent Variable: Modern Technology Index