ADVANCING THE UNDERSTANDING OF POLICE CRIME FROM A STRUCTURAL PERSPECTIVE: AN ANALYSIS OF AMERICAN COUNTIES

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ABSTRACT

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Decades of misconduct and crime committed by law enforcement officers throughout the United States have been uncovered by investigative journalism, independent commissions, and ethnographic research. Theoretical studies identify that individual and cultural factors are significantly related to an officer's participation in criminal behavior. There exists a lack of complete understanding of how an officer's community and environment may influence their participation in police crime. The purpose of this dissertation is to advance the field of criminology by expanding the structural level understanding of police crime through a theoretical lens and quantitative approach on a national scale.

Drawing from social disorganization theory, five nationwide datasets are merged to construct a longitudinal, panel dataset that describes police crime throughout American counties. Using a structural level theoretical perspective, this project broadly explores how the characteristics of American counties may be associated with the criminal behaviors of police officers. The tenets of social disorganization theory suggest that counties with antecedents of social disorganization (such as characteristics of poverty, transient populations, and low educational attainment) should be associated with higher counts of police crime and general crime.

Three research questions are investigated in this dissertation. The first two analytical chapters ask the following research questions: First, do county level variables correlate with counts of police crime? Second, are the correlates of general crime the same for police crime at a

structural level? I construct and compare mixed-effects models regressing police crime and general crime onto county level variables. A comparison of these models informs a discussion about the structural similarities and differences between police crime and general crime. These findings inform the final analytical chapter, which explores the potentially interwoven relationship between police crime and general crime. The third research question explores whether general crime has a significant relationship with police crime. The complexities of this relationship inform a thorough discussion of policy implications associated with reducing police crime throughout the United States.

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CHAPTER I. INTRODUCTION

The current public discourse about American policing challenges the accountability and integrity of law enforcement officers. There exist polarizing opinions regarding this debate. Public opinion polls draw extreme responses in opposition to the legitimacy of the profession. The Associated Press found a stark increase in the percentage of Americans who identified police violence as a “serious problem” and a poll from the Washington Post revealed the majority of respondents do not have confidence regarding use of force police training (Berman & Clement, 2023; Stafford & Fingerhut, 2020). Scholars have agreed that high-profile cases of excessive use of force trigger a powerful response from the general public, including surges of widescale protests and negative media attention (Moule et al., 2019; Wolfe & Nix, 2016). This polarizing media coverage might cultivate unwarranted fear and distrust of police across America (Pickett et al., 2022). Following these incidents, research has found that police are increasingly scrutinized, overall satisfaction with local police has decreased, the satisfaction with police accountability has decreased, and there exists an ongoing tension between police and their communities (De Angelis & Wolf, 2016; Moule et al., 2019; Weitzer, 2002; Wolfe & Nix, 2016). Researchers have deemed the current state of American policing to be a crisis of legitimacy (Wolfe & Nix, 2016).

The combination of lack of trust and absence of accountability has led many Americans to scrutinize the police. An exigent wave of scrutiny surrounding police accountability and legitimacy emerged following the death of Eric Garner at the hands of several New York City (NY) police officers in July of 2014. Ferguson (MO) police killed Michael Brown less than a month later, again sparking civil unrest and protests across the country. Tamir Rice, a 12-year-old, was killed by Cleveland (OH) police officers just over three months later. Each of these incidents were found to be legally justified, and the officers involved in these incidents were not criminally charged. In less than five months, three high-profile violent fatalities by law enforcement officers prompted many Americans to demand immediate action and accountability. Researchers recognize that widescale media interest, public protest, and growing political attention consistently led to the following conclusion: “a nontrivial portion of the public wants change in law enforcement” (Wolfe & Nix, 2016). The growing attention to this crisis emphasizes the importance of developing well-informed, empirically and theoretically based policies for police officers in America.

Since these incidents, there has remained a pattern of civil unrest and demands for change. Nearly a decade later, the same calls for action have been met with little to no changes in many aspects of American policing. In 2020, another surging wave of public outrage arose after a video circulated the internet of a Minneapolis (MN) police officer murdering George Floyd by kneeling on his neck for over nine minutes. The inaction of several surrounding officers guarded the horrific incident, as a crowd of concerned people watched this tragic death. The criminal indictments and convictions of these officers served as a rare incident of accountability. Today, patterns of outrage, protests, and civil unrest continue to follow violent police encounters; however, history reveals the warranted skepticism about changes in American policing.

Policing in America has been publicly scrutinized for decades. Although the majority of the public still supports law enforcement officers, there exists overwhelming waves of outrage following high profile incidents or fatalities (see Berman & Clement, 2023). Media coverage of police violence and corruption may socially construct a fear which is only weakly tethered to reality in many communities (Pickett et al., 2022). The fatalities at the hands of law enforcement officers within the recent years have reignited the same public outrage from the 1960s. Police brutality, misconduct, and crime are not new experiences, yet failure to achieve meaningful changes has motivated the public's demand for accountability. For decades, scholars have been studying this phenomenon.

Criminologists began using traditional criminological individual level theories to explain police misconduct and criminal behavior. A variety of theoretical frameworks have been found helpful to explain police deviance, most notably theories of strain, control, and learning perspectives (Donner et al., 2021). Bishopp and colleagues have consistently found that the demands of the job coupled with organizational structures, rules, and procedures play a role in the lives of law enforcement officers (Bishopp et al., 2016, 2019, 2020). Furthermore, research has shown higher levels of stress and strain correlate with measures of police misconduct (Bishopp et al., 2016). Control theorists suggest self-control can partly explain an officer's participation in deviant behavior and also explains why officers may adhere to the "code of silence" and fail to report their peers (Donner et al., 2016a; Donner et al., 2018; Donner & Jennings, 2014). These theorists have found that traditional criminological theories serve well as a starting point for understanding deviance specific to American policing. Criminologists have noted that the field should expand upon individual level perspectives to examine how officers may acquire or learn deviance from their social network (Wood et al., 2019). Building on this body of literature, scholars have recognized the unique characteristics of police work that would call for additional explanations beyond micro level criminological theories.

American policing is built on high levels of discretion and justified violence. Historically, citizens trusted the police with these discretionary practices, yet skepticism surrounding officers' integrity prompted further interest in these factors unique to police work (Fridell, 2010). Beyond individual level theories, scholars have expanded their lens to examine occupational and cultural factors that may influence police crime. Criminologists have recognized that police officers have the unique opportunity to diminish or justify their criminal behaviors by the "cloak of their authority" (Donner et al., 2021, p. 831).

Scholars have yet to thoroughly explore how this preexisting literature about individual level and occupational explanations of police crime couples with structural level factors. Kane was the first criminologist, to my knowledge, to quantitatively examine the structural level factors through his examination of social ecology of police crime (2002). His research found support for his ideas and suggested the need for additional research continuing his examination of social disorganization as it relates to police crime and deviance (Kane, 2002). Furthermore, scholars have recognized the importance of more macro level theories but have limited their own research due to the dearth of current data (Donner et al., 2021). Expanding empirical research with macro theoretical perspectives will allow criminologists to integrate individual level and structural level theories to gain a better understanding of police deviance, misconduct, and crime.

Prior research about police crime has been hindered by the lack of quality data. Research is often reliant on data from individual jurisdictions because there are no official data capturing the behaviors of law enforcement officers on a national scale (Stinson, 2020). This fundamentally limits the scope of the theoretical perspectives that could be applied in these studies. This dissertation confronts these limitations of current literature by merging several datasets to expand the understanding of structural level explanations of police crime.

This dissertation initiates structural level nationwide research aimed at improving policing in America by understanding the county level correlates of police crime. Although this dissertation is the first quantitative study to explore the structural level explanations for police crime on a national scale to my knowledge, it is important to first recognize the prior literature that grounds this research. Chapter II will provide a brief summary about the history of police crime in America, explore the methodological challenges of studying police crime, and lastly, will recognize several theoretical frameworks aimed at explaining police deviance, misconduct, and crime. Chapter III will provide a succinct summary of the current study and offer hypotheses.

This dissertation will employ five datasets to explore a series of research questions. Data from the Uniform Crime Reporting (UCR) program, the American Community Survey (ACS), the Census of State and Local Law Enforcement Agencies (CSLLEA), and the United States Department of Agriculture – Economic Research Service will be merged by county-years to the data of the Henry A. Wallace Police Crime Database. The data and measures of this newly constructed, nationwide, longitudinal, panel dataset of American counties will be explored in Chapter IV.

The following three analytical chapters will yield important findings. Chapter V aims to answer the following research question: Do county level variables correlate with police crime (RQ1)? Counts of county level police crime will be regressed on county level variables using a series of mixed-effects models. I will answer the research question through a model building process that employs these versatile statistical models intended for longitudinal data. I include a further discussion of the analytical strategy at the start of each analytical chapter.

Chapter VI will then explore whether these correlates of police crime are the same for general crime with the following research question: Are the correlates of general crime the same for police crime at a structural level (RQ2)? I will further examine whether there are unique predictors of police crime (or general crime) at a county level. A series of mixed-effects models will regress counts of county level general crime onto the same predictors as the prior chapter's models. I then compare these models to determine similarities and differences.

Chapter VII will then explore whether general crime correlates with police crime by examining the following research questions: Does general crime have a significant relationship with police crime (RQ3)? Furthermore, I will examine whether specific types of general crime significantly correlate with police crime. I employ a similar analytical approach as the prior two chapters with the addition of a focal independent variable of general crime, lagged by one year. Police crime will be regressed on these predictors using a series of mixed-effects models. Additional explorations of specific types of general crime, also lagged, are explored throughout this analytical chapter. Lastly, I also employ mixed-effects regression models that regress general crime on a lagged police crime variable with other predictors. This series of models completes my thorough exploration of the potentially complex relationship between general crime and police crime.

These predictive models will determine whether structural level theories of police crime throughout the United States are a valuable approach. Grounded in a sociological perspective, this dissertation aims to advance the study of police crime by complementing the current literature focused on individual level criminological theories of police crime with a more macro lens. Lastly, in the concluding chapter (Chapter VIII), meaningful policy implications will demonstrate how these findings can be used to advance the knowledge of police crime and develop evidence-based policies aimed at improving policing.

CHAPTER II. LITERATURE REVIEW

History of Police Crime Research

American policing is heavily scrutinized by the public. The current criticisms often speculate about the lack of accountability and integrity of law enforcement officers. These concerns often relate to presumed misconduct and crime committed by law enforcement officers under the cloak of their authority. The line of research examining this phenomenon dates back decades.

Issues concerning American policing are not a new experience. Police crime and corruption have been occurring for over a century. The systemic secrecy of the policing subculture has always allowed for police corruption and crime to thrive (Stinson, 2020). The Wickersham Commission reported that corrupt methods of law enforcement date back to Prohibition. They found, “illegal and corrupt methods of enforcement throughout a long period in the decade of national prohibition have been proximate causes of an extensive public sentiment against the enforceability of this law that is generally prevalent at this time” (National Commission on Law Observance and Enforcement, 1931, p. 274). This is one of the earliest written reports expressing public uncertainties with American policing practices. A researcher wrote similar concerns about American police and their role in corruption during Prohibition. He expressed grave concern about the “elaborate underworld organization” that controls illicit gambling, alcohol distribution, and protection for brothels and speakeasies (Key, 1935, p. 628). An informal silence among officers allows for the corruption and control to continue (Key, 1935). During this time, the Supreme Court of the United States was declaring formal boundaries of police practices while enacting prohibition laws. *Carroll v. United States* declared that warrantless searches and seizures of vehicles were constitutional only when probable cause was found (1925). American policing experienced significant scrutiny throughout the 1920s and 1930s as there were legal changes and the public began to question their authority.

A prominent shift occurred in the 1960s for law enforcement in the United States. Police were expected to maintain order throughout the civil rights movement, protests, and riots which meant police patrol were often placed in defensive situations (Albrecht, 2017, p. 9). These defensive situations led to alleged misconduct toward specific groups. Minority groups, advocates, and media alleged excessive use of force by law enforcement during this time (Mara, 2010). The clear inconsistencies in treatment led groups to question their confidence and trust in law enforcement. The potential of unjust policing has casted fear over many Americans (Pickett et al., 2022). The distrust of police by minority populations has created a racial divide in the overall support for the police (Berman & Clement, 2023; Pickett et al., 2022). This movement ultimately changed how the public views law enforcement.

The general public began to question the discretionary nature of police work in the 1960s, in line with the civil rights movement. Most Americans did not see police discretion as a potential problem prior to the civil rights movement (Fridell, 2010, p. 33). The attention drawn to inconsistencies in treatment led agencies to refine their policies and practices. This movement greatly impacted the tactics and policies of the New York City Police Department and many other agencies across the country (Albrecht, 2017, p. 10). Regulations, guidelines, and training materials were developed and formalized during this time.

During this time, the United States Supreme Court ruled on several cases which also altered police discretion and authority. *Elkins v. United States* (1960) and *Rios v. United* States (1960) eliminated the ability for federal prosecutors to use evidence during criminal trials which may have been obtained by illegal or unreasonable searches and seizures. *Mapp v. Ohio* (1961) applied these findings to the states and concluded any evidence illegally obtained cannot be used against the accused in court. *Miranda v. Arizona* (1966) ruled that evidence obtained through interrogations cannot be used in against a defendant without an adequate demonstration that their rights were given and knowingly and intelligently waived. *Terry v. Ohio* (1968) sustained that police may "stop and frisk" individuals when they have articulable facts that support a reasonable suspicion of criminal behavior. *Chimel v. California* (1969) ruled that warrantless searches of the entire home are not constitutional after an arrest is made inside the home. Each of these court decisions refined the authority of law enforcement. These cases altered how police conducted their daily duties and required that police must act justly and within citizens' legal rights. These decisions provided clear direction for police and significantly transformed the profession throughout the United States.

Independent commissions are often tasked to examine police agencies. The first reported systematic observation of police patrol was completed in 1966 for the President's Crime Commission on Law and Administration of Justice (1967), also known as the Katzenbach Commission (Walker, 2010, p. 3). Systematic social observation (SSO) has been deemed an integral part of social science (*Systematic Observation of Public Police: Applying Field Research Methods to Policy Issues*, 1998). Observing police actions allows researchers the ability to explore a perspective that suggests police behaviors may be controlled by administrative policies (Walker, 2010, p. 5). Recent reflections on this commission's findings noted that the lack of operational data on police agencies made it entirely impossible to "fight crime" (Feucht & Zedlewski, 2019). Thus, agencies cannot properly serve their communities unless they are maintaining good data that could be used to assess their practices. Without data, leadership cannot see the possible systemic patterns of corruption and misconduct within their departments.

This commission brought to light that as research about police crime and misconduct continues, agencies should be open to observation as it provides valuable insights in professional development and improves policing (Walker, 2010, p. 3). Independent commissions have played an integral role in policing research for decades and have advanced our understanding of police corruption, misconduct, and crime.

Independent commissions often were in direct response to police scandals that caused the agency to be under scrutiny. These commissions were often established by state or city officials to investigate specific allegations of police corruption or deviance after a public outcry (Stinson et al., 2016). The Commission to Investigate Alleged Police Corruption (1972), also known as the Knapp Commission, was charged with examining the corruption of the New York City Police Department (NYPD). The commission concluded the corruption in NYPD was widespread but by no means uniform in nature (Commission to Investigate Alleged Police Corruption, 1972). Police corruption and misconduct were not new problems for the NYPD but rather occurred on a cyclical pattern of scandal and reform (Kane & White, 2012). The commission ultimately concluded that the corruption was highly organized (Fyfe & Kane, 2006). The “stubbornness, hostility, and pride” of law enforcement agencies became an obstacle that prevented meaningful reform (Commission to Investigate Alleged Police Corruption, 1972, p. 6). This obstacle appears to become a pattern as similar concerns were present in the Philadelphia Police Department a few years later. Police chiefs could no longer terminate their “problem officers” or “bad apples” and deem the issue as solved. It seemed as though the corruption was rooted much deeper.

The Knapp Commission found several forms of non-violent corruption within NYPD. They distinguished two specific types of corrupt behavior by New York law enforcement officers, “grass eaters” and “meat eaters” (Commission to Investigate Alleged Police Corruption, 1972). The “grass eaters” often participated in petty corrupt behavior, whereas the “meat eaters” were often engaging in more aggressive, exploitative behaviors (Commission to Investigate Alleged Police Corruption, 1972). Of those corrupt officers, the vast majority consisted of “grass eaters,” engaging in everyday corruption, however the prior focus of solving the underlying corruption problem was placed on catching the “meat eaters” (Armstrong, 2012). Meanwhile, the “grass eaters” were often flying under the radar because there was no system in place to catch or prevent these lesser corrupt behaviors. Therefore, the corruption within the NYPD continued.

Shortly after the Knapp Commission, the Pennsylvania Crime Commission was tasked with examining police corruption and misconduct in Philadelphia. This commission found that the corruption was “ongoing, widespread, systematic, and occurring at all levels” (Pennsylvania’s Crime Commission, 1974, p. 96). They concluded the departmental corruption “plagued the force since its inception” (Pennsylvania’s Crime Commission, 1974, p. 96). The commission report speculated how such a corrupt environment came to be. They conjectured that the department’s own attitude toward corruption and the societal pressures placed on individual officers made for an impossible fight against the problem (Pennsylvania’s Crime Commission, 1974). The report states, “it is impossible to fight successfully a problem that the leadership will not acknowledge exists” (Pennsylvania’s Crime Commission, 1974, p. 109). This statement comes from the fact that leadership within the department did not recognize the issue as a departmental problem, but rather a problem of “rotten apples.” This commission found solid evidence against this notion. Independent commissions of the 1960s and 1970s made it very clear the police corruption was a widespread pattern of behavior. These patterns of misconduct were not unique to one city or agency and certainly not isolated to a few “rotten apples.”

Building on the literature and knowledge of the 1960s, Fyfe and then graduate student Kane began a two-decade-long project examining police misconduct. Following the findings of the Knapp Commission and the Pennsylvania Crime Commission, they knew there was work to be done. Spanning from 1975 to 1996, this study produced a variety of fruitful findings still being discussed decades later. The purpose of this study was to explore the nature and prevalence of police misconduct and identify the factors that may distinguish corrupt officers from their colleagues (Fyfe & Kane, 2006). They concluded this study by suggesting to the agency to "hire *good people* with clean histories and good educations" and supervise them carefully (Fyfe & Kane, 2006). This conclusion could be skewed by researchers to suggest that "bad apples" in policing are a product of low hiring standards (Stinson, 2020, p. 66). Rather, Fyfe and Kane elaborated that smaller internal disciplinary behaviors could escalate into career-ending misconduct if not handled carefully (Fyfe & Kane, 2006). This would further discredit the idea that police misconduct is more than just a few "bad apples," and is rather built within an agency's policies and culture.

Kane continued his work with this study, presenting a new, critical perspective with colleague White. They reflect on the findings of the Knapp Commission and deem the "real problem" as those grass-eater police officers who foster the culture that corruption, at any level, is acceptable (Kane & White, 2012). The lack of accountability and unwillingness of other officers to defy others' corruption, or the "code of silence," proved to be true in several incidents. This prevented the few motivated police officers from making significant reforms to correct the problem from within (Kane & White, 2012). Furthermore, their data showed that NYPD, in a way, created their own misconduct by failing to properly vet their new hires and officers (Kane & White, 2012). This would imply that the failure to police the police may be exacerbating the acceptance of misconduct and corruption within the agency.

Kane and White's reflection on the original study revealed several shortcomings. They specifically acknowledged the data cannot show the true prevalence of police misconduct. This limitation is rooted in two methodological issues. First, definitions of "police misconduct" are inconsistent throughout research. Second, data are not available to the proper researchers and departments are traditionally unwilling to engage in these types of research (Kane & White, 2012). These methodological shortcomings will be discussed in more detail further into this chapter. Kane and White also revealed that, beyond the methodological issues, there exists an issue involving the lack of theoretical perspectives used within this field of research. At the time of their research, there had been very few applications of criminological theory studying police misconduct (Kane & White, 2012, p. 123). Rather than focusing on the prevalence of police misconduct, it seemed as though researchers were beginning to shift their focus to understanding the theoretical explanations and determining how agencies might be able to utilize these criminological theories to inform their policies and practices (Kane & White, 2012). Despite the potential methodological confusions, there appeared to be a growing interest in this field of research with a new focus on criminological theory. I will discuss several theoretical perspectives later in this chapter. The various findings from Kane and White's study advanced literature on American policing greatly, but also revealed how much further we have yet to go. In the years since this project was published, scholars continue to understand police crime and misconduct through several old and new methods.

The egregious assault and beating of Rodney King shocked the nation as it was the first highly viewed video recorded incident of police excessive use of force. The incident occurred early in the morning in March 1991. The Report of the Independent Commission on the Los Angeles Police Department (1991), also known as the Christopher Commission, recounts the incident, which prompted the investigation and commission report. Police attempted to pull over King for speeding and after King eluded the police, a highspeed pursuit occurred. King was eventually cornered by police cruisers and was ordered out of his vehicle. A nearby bystander began recording the incident. The video showed four Los Angeles police officers hitting King with their batons repeatedly, including hits to his wrists, knees, ankles, and elbows. The officers continued to kick, handcuff, and drag King across the street despite him being very visibly injured. The bystander offered the video to local and national media, after the Los Angeles Police Department declined the video. This was the first "raw display of police brutality" that many Americans witnessed and the video served as a form of "street justice" (Stinson, 2020, p. 81). This horrific incident sparked sudden public outrage, protests, and a call for action.

The Christopher Commission was tasked with investigating the conduct of the Los Angeles Police Department (LAPD) following the beating of Rodney King. Citizens were left with many fundamental questions about the LAPD, including questions about its overall culture, failure to control and discipline officers, inability to screen out applicants with a propensity to violence, and the role of LAPD leadership (Report of the Independent Commission on the Los Angeles Police Department, 1991). The report revealed that several police officers had extremely high rates of excessive force complaints from citizens and found stark racial and ethnic biases among the surveyed officers (Report of the Independent Commission on the Los Angeles Police Department, 1991). Following this report, federal legislation required data to be collected and an annual summary disseminated on the use of force of police officers, yet we can speculated that these data were never collected due to the lack of a summary report being published in over three decades since this legislation was mandated (Stinson, 2020). Despite several problematic findings, there appears to be insufficient progress being made by law enforcement agencies.

A few short years later, the Commission to Investigate Allegations of Police Corruption and the Anti-Corruption Procedures of the Police Department (1994), also known as the Mollen Commission, was tasked with again examining the allegations of misconduct by the New York City Police Department. This commission concluded that despite the findings of the Knapp Commission decades earlier, corruption still prevailed in the New York City Police Department. The overall nature of the corruption in the department changed over these decades (Stinson, 2020, p. 26). This commission now found that the more prevalent form of corruption was much more intense than the formerly predominant petty corruption that existed in the 1960s. The levels of corruption seemed to have escalated over the previous decades. The Mollen Commission concluded that the corruption took numerous forms, including officers heavily involved in the drug trade, high rates of police brutality and violence, officers participating in bribery and theft, and general abuses of their authority (1994). The morals, values, and principles of the officers have been eroded, making for a culture susceptible for corruption (Commission to Investigate Allegations of Police Corruption and the Anti-Corruption Procedures of the Police Department, 1994). The dishonest cops do not fear their honest colleagues. Honest, non-corrupt officers still contribute to the corruption by failing to break the “code of silence” used to protect corrupt cops (Commission to Investigate Allegations of Police Corruption and the Anti-Corruption Procedures of the Police Department, 1994). This informal rule of silence dates back decades (see Key, 1935). A reflection on this commission stated any attempts at controlling corruption would be entirely unsuccessful without a transformation of police culture (Baer & Armao, 1995). This commission revealed the tragic state of American policing in the 1990s.

The tragic cycle continues into recent years. Researchers have deemed police misconduct, “one of the greatest threats to the protections extended to citizens in a free and democratic society” (Kappeler et al., 1998, p. 3). High-profile cases are promptly met with a wave of protests, public outrage, and calls for reform. Gradually, conversations about policing in America have turned hostile and antagonistic. Political extremism has exacerbated the arguments surrounding the legitimacy of policing in the criminal legal system (LaFree, 2021). Polarized political environments have exacerbated the divide among attitudes toward American police (Reny & Newman, 2021). Following a high-profile incident involving the Ferguson Police Department in Missouri, a report by the United States Department of Justice concluded an undeniable lack of trust by citizens, specifically of minority groups (2015). Furthermore, the department’s internal affairs practices fail to serve as a mechanism to restore citizens’ trust and further solidify the department’s lack of accountability for its officers (Investigation of the Ferguson Police Department, 2015). The crisis of accountability and legitimacy in American policing is still prominent.

Law enforcement officers in America are often exempt from accountability and consequences for their corrupt actions. By the nature of their duties, police officers are legally allowed to use force against citizens (Stinson, 2020). The decentralized nature of American policing results in several thousand use of force policies, each with different structures and procedures (Pate & Fridell, 1993). The control of these policies lies within the same municipal, county, and states governments that create them (Pate & Fridell, 1993). The public has not always questioned the discretionary nature of this violence (Fridell, 2010). Rather, the basic structure of American policing allows the opportunity for rogue officers to engage in unjustified violence without the threat of accountability (Stinson, 2020). Police officers are not closely watched throughout their working hours by supervisors, victims of police violence rarely report the abuse, and citizen complaints are not often believed (Stinson, 2020). Furthermore, police agencies may be hesitant to acknowledge excessive use of force for fear of damaging the officer's and agency's reputation and for concerns of civil liability (Pate & Fridell, 1993). This myriad of circumstances has led to the lack of accountability of American law enforcement officers. Consequentially, a portion of the general public has remained distrustful and skeptical of American policing and the overall lack of accountability for its officers.

The lack of data about police agencies, officers, and current policing policies have remained a roadblock in current research. Data-driven policies cannot exist without accessible data and agencies' willingness to work with researchers. In recent decades there have been several public claims by legislators that they are aware of this ongoing demand, yet all have fallen short. In 2015, Former President Obama's Task Force on 21st Century Policing recommended provisions for the collection of demographic data, including the public access to these data to ensure transparency (2015). The George Floyd Justice in Policing Act (2021) called for legislation aimed at enhancing the transparency and data collection of police misconduct in the United States in 2021. In 2022, the White House released an executive order about advancing effective and accountable policing (Executive Order on Advancing Effective, Accountable Policing and Criminal Justice Practices to Enhance Public Trust and Public Safety, 2022). In a 2023 request for information associated with this order, it was stated, "building trust in policing and criminal justice requires transparency through data collection and public reporting" (Request for Information; Criminal Justice Statistics, 2023). The persistent call for data-driven policing policies has not been met with any substantial nationwide action. The following section will explore some methodological challenges associated with policing research in America currently.

Methodological Challenges

There are two main methodological challenges researchers have faced when studying police crime. First, there is an absence of adequate data. Second, researchers have not consistently used a clear conceptual definition of "police crime" or "police misconduct" and furthermore, they have not always found an adequate way to operationalize this measure. These methodological challenges have remained a hindrance for advancing the current literature about police crime, yet researchers have still found creative ways to evolve this field of literature.

The first methodological challenge in studying police crime or misconduct is the clear lack of data. This concern with inadequate police data has highlighted the overall lack of information about police agencies known to the public. To my knowledge, nationwide public information about certifications, training, calls-for-service, or officer demographics does not exist. Furthermore, there are no nationwide official data about citizen's complaints about officers, de-certifications, nor police misconduct and crime. Current claims by the government to collect data on police misconduct and crime are largely a response to the "political crime-control rhetoric to stem moral panics and public outrage" after a high-profile publicized case (Stinson, 2020, p. 25). Official government efforts to "collect, analyze, and disseminate information" specifically about police crime have remained unsuccessful (Stinson, 2020, p. 25).

Researchers have been left to use non-official, non-representative data sources to attempt to make sense of the larger, nationwide issue that America is facing today. Data retrieved from investigative journalism, independent commissions, civil rights organizations, observational field research, or data from single jurisdictions, cities, or states fail to capture the full nature of policing in America. Investigative journalism, independent commissions, and civil rights organizations often yield large amounts of information about police misconduct, yet often focus their efforts closely on high-profile incidents within a specific jurisdiction (Stinson, 2020). The dissemination of these data often yields strong reactions and emotions from the general public, but often fails to make any meaningful changes within policing policies. Policy makers can minimize observational field research because these data may not be generalizable to policing in other jurisdictions at other times (Stinson, 2020). Extensive literature using these imperfect data prove that researchers are eager to study issues of American policing. It is evident that the call for these empirically based policies exists, yet the lack of data makes this a difficult issue to solve.

The approach of studying national-level questions with data that is not nationwide is clearly limited. This limitation largely explains why criminologists have yet to explore police crime through a community-level framework on a national scale. Despite this methodological challenge, researchers have been eager to explore individual level theories to explain police crime. These theories will be discussed in the following section of the literature review.

The second methodological challenge is the conceptual confusion when studying police crime or misconduct. There are many terms used to describe law enforcement officers engaging in criminal or deviant behaviors. Corruption, crime, misconduct, violence, excessive use of force, and abuse of authority can all describe different forms of police deviance (Albrecht, 2017). The study of this overall field has been hindered by the conceptual confusion and lack of consistency for these related terms (Stinson, 2020). The difficulties in defining police misconduct are partly produced by the lack of reliable data available to researchers (Donner et al., 2021). Albrecht acknowledges there is a spectrum of deviant police behaviors (2017). It is important to recognize this discrepancy throughout the field of research.

Researchers use a variety of conceptual definitions to describe deviant or criminal behaviors of law enforcement officers. Conceptual definitions are used to clarify what we mean by a stated concept (Adler & Clark, 2015). In a review article, Donner et al. (2021) found there was a wide variety of conceptual definitions used to define police misconduct. Kane and White provide examples of whether some thought-provoking scenarios should be defined as police misconduct (2012, pp. 6–7). Some of these scenarios include an off-duty officer stealing from a convenience store. Would it make a difference whether they were in street clothes or their police uniform? What if they used their service weapon to threaten the employee? Another scenario includes several police officers accepting a free cup of coffee. Could this be considered accepting a bribe? Are they providing any preferential treatment for the coffee shop owner? Other scenarios to consider are incidents that may not be illegal but could be deemed as misconduct such as repeatedly losing your police badge or identification or abusing departmental policies. Kane and White recognize the importance of having a methodological discussion about these determinations prior to jumping into any research project (2012). Although this can often be seen as a limitation in literature, it can also be seen as the nature of research that is gradually becoming more refined as the field of study advances. Beyond the conceptualization of definitions, researchers are tasked with operationalizing their definitions.

Operationalizing a concept goes beyond clarifying the definition and focuses on how the variable will ultimately be measured. The operationalization of a variable can be described as "the process of specifying what particular indicator(s) one will use for a variable" (Adler & Clark, 2015, p. 127). These operational definitions of police crime or police misconduct will determine how the researcher measures this concept. For example, are they looking at how many times an officer was arrested or how many times they were disciplined by their agency?

Researchers should consider that police officers are "legally allowed to use reasonable force to maintain order and public safety and to take suspects into custody" (Stinson, 2020, p. 16). This makes it difficult for researchers to distinguish justified, legal uses of force from illegal acts of police violence (Stinson, 2020). Furthermore, research will often rely on the criminal rulings of judges, juries, or prosecutors to determine what is classified as "crime," when in reality, the general public often disagrees with these judgments. These examples are fairly basic, and like Kane and White suggested, methodological discussions should more intensively cover potential confusions. Invalid operational definitions and variables that do not measure what they are intended to cause problems when drawing appropriate conclusions (Kalof et al., 2008). The accuracy and precision of details of the operationalization should be of the utmost importance to the researcher as the internal validity of the research could be at risk.

The conceptualization and operationalization of variables allow researchers to more clearly demonstrate their findings. The inconsistencies in reported prevalence of police crime and misconduct are largely due to the inconsistencies of operational definitions and the source of the data (Donner et al., 2021). For example, some researchers may be reporting police crime as the number of criminal arrests of law enforcement officers and others may be reporting the number of citizen use of force complaints. The blatant inconsistencies cause conceptual confusion within the field. By recognizing the distinctions in definitions, researchers should be able to more clearly and properly incorporate theoretical frameworks into their studies (Albrecht, 2017). This methodological challenge has hindered the overall study of police crime and should continue to be explicitly discussed throughout research. Despite these challenges, researchers have continued to evolve this field of research and the following section discusses the theoretical advancements of police crime literature.

Theoretical Frameworks Explaining Police Misconduct

Similar to the general public, academia and researchers have experienced a growing interest in police crime and corruption. Over the past century, but more prominently in recent decades, researchers have begun to explore police officers' corrupt, deviant, and criminal behaviors through a theoretical lens.

Individual level theories

The emerging field of literature that uses criminological theories to explain police behavior has explored an abundance of individual level theories. A review article found that criminologists have primarily used these theories to explain police misconduct, rather than more macro level theories (Donner et al., 2021). Individual level criminological theories focus on an individual's attitudes, beliefs, and other individual level factors to explain their criminal behavior.

Social learning theory

The origins of Akers' social learning theory are rooted in Sutherland's differential association theory. Differential association theory posits that criminal behaviors are learned in a social process of symbolic interaction with others (Sutherland, 1933, 1939, 1947). Burgess and Akers built upon Sutherland's conceptualization and specified the learning mechanisms (1966). Using principles from these previous versions, Akers developed his social learning theory. This theory describes that criminal and deviant behaviors are learned through four main principles: differential association, definitions, reinforcement, and imitation (Akers, 1973, 1998). When applied to police crime, theorists suggest that criminal police behaviors are specifically learned through symbolic interactions with fellow police officers (Chappell & Piquero, 2004).

Applications of social learning theory to explain police crime and misconduct focus on the learning networks of police officers. The first application of social learning theory in this field of literature, to my knowledge, was Chappell and Piquero examining how Philadelphia officers learn from their peers to accept gifts, commit opportunistic theft, and use excessive force (2004). They build on the deviant subculture narrative alluded to throughout reports from independent commissions and suggest that officers may be grouping into deviant peer groups (Chappell & Piquero, 2004). Other researchers expanded upon the "bad apple" narrative suggesting that these individuals may teach their deviant ways to their peers (Wood et al., 2019). A study of Chicago law enforcement officers concluded that "police misconduct appears to be a networked phenomenon" because they were able to string together various patterns of misconduct based on policing districts (Wood et al., 2019, p. 13). The process of police socialization could explain how a "bad apples" narrative could be transformed into a "deviant subculture." This idea is explored further later in this chapter. In summary, scholars have found support for social learning theories in a multitude of contexts involving police crime and misconduct. Many aspects of these applications of social learning theory have common elements with another criminological theory focused on social attachments.

Social control theory

Social control theory is built on the underlying assumption that criminal acts are a result of an individual's weak or broken attachments to conventional society. These attachments, or ties to non-criminal behaviors, are explained by four main elements: attachment to pro-social individuals, commitment and desire to achieve conventional goals, involvement in conventional activities, and belief in societal values (Hirschi, 1969). Criminologists have long used this theory to explain criminal behaviors of individuals. When applying this theory to longitudinal, panel data, Agnew found general support for this theory, but the social control variables only explained limited variance (Agnew, 1985). This would suggest this theory cannot be the sole explanation for criminal behavior. Despite the importance of this theory, researchers remained in support of this theory with necessary caution specifically when interpreting the results (Agnew, 1991; Krohn & Massey, 1980; Massey & Krohn, 1986). Scholars still recognize the importance and significance of this theory (Costello & Laub, 2020).

Adaptations of this theory have been used to explain delinquency and crime for specific groups. Criminologists have applied this theory to forms of occupational misconduct (Green, 1990). In this specific adaptation of the theory, the element of involvement in conventional activities cannot adequately be explored. This is due to the fact that involvement in a career cannot prevent misconduct that occurs in that career (Green, 1990). Criminologists have further adapted this theory to examine crime by law enforcement officers. In this specific application of the theory, researchers examine whether the attachment to pro-social individuals, commitment and desire to achieve conventional goals, and belief in societal values would be associated with police crime (see Donner et al., 2016b; Fridell et al., 2021; Zavala & Kurtz, 2016). Researchers found support for social control theory in a study of police supervisors from three large agencies. This study measured social attachments as the consequences, both personal and professional, they would face if caught engaging in misconduct (Donner et al., 2016b). They ultimately concluded that police supervisors who were able to list more social attachments had lower intentions of engaging in criminal behaviors (Donner et al., 2016b). This would suggest that police supervisors with more social attachments were less likely to jeopardize their stakes in conformity by engaging in corruption or misconduct.

Literature explicitly applying social control theory to police misconduct is scarce. Another study used social support and bonds with friends and family to predict problematic alcohol consumption by police officers (Zavala & Kurtz, 2016). Although this is not a precise application of social control theory, this study yields valuable findings. They concluded that stronger social bonds led to smaller likelihood of engaging in problematic alcohol consumption; however greater levels of social support inherent to police work were associated with a greater likelihood of engaging in problematic alcohol consumption (Zavala & Kurtz, 2016). The findings of this study reveal a new, complex approach of applying theories of social support and attachment to police work.

Deterrence theory

Deterrence theorists believe that it's the rational fear of punishment that prevents individuals from committing crimes. This theoretical perspective focuses on what might deter individuals from criminal behaviors, rather than theorizing why individuals are more inclined to commit crimes (Clarke & Cornish, 1985; Cornish & Clarke, 1987). Criminologists apply this theory to police crime.

Through a study that examined the attitudes of police officers, scholars found that deterrent factors, in concept, might discourage officers' attitudes towards misconduct. This study concluded that agencies with unfair punishments and uncertainty of detection were associated with more positive, accepting views of police misconduct (Fridell et al., 2021). This would suggest that agencies with efficient and effective processes of detection and proportional severe punishments would likely retain officers with attitudes against misconduct (Donner et al., 2021; Fridell et al., 2021). However, scholars could argue that police officers may not be deterred if the punishments do not outweigh the misconduct (Stinson, 2020). Furthermore, prior research has found the severity of punishments are not significantly associated with attitudes towards misconduct among police officers (Fridell et al., 2021). As such, deterrence theory does not seem to hold the strongest support for explaining police crime. However, in concept, the attitudes of officers may be deterred based on effective processes of detection and punishment.

General theory of crime (self-control theory)

Theories of self-control recognize that people may be vulnerable to the temptations of criminal or deviant behaviors. Gottfredson and Hirschi theorize that criminality can be explained by low self-control (1990). They further elaborate that deviant and criminal opportunities are ever present and it's an individual's self-control that governs their propensity to engage in this behavior (Gottfredson & Hirschi, 1990). Gottfredson and Hirschi focused their conceptualization of self-control on long-term costs of a behavior, but after criticism of the original definition, Hirschi reconceptualized self-control to consider all costs associated with a behavior, including perceptions and importance of costs (Gottfredson & Hirschi, 1990; Hirschi, 2004). Self-control theory has generated the most literature of all individual level theories of police crime.

Donner and colleagues have piloted several applications of self-control theory to police crime. Donner's dissertation was the first of his work to find support for this theory when applied to police crime. He concluded that measures of self-control were significantly correlated with both prior, and the likelihood of future, police misconduct (Donner, 2013). His ongoing work remains in support of self-control theory, but posits it cannot unequivocally explain all police misconduct (Donner & Jennings, 2014). In an application of self-control theory from Donner and colleagues, they concluded that low levels of self-control were significantly correlated with four out of six forms of misconduct (2014). They did not find self-control to be significantly correlated with lack of service complaints or departmental disciplines (Donner & Jennings, 2014). His other work concluded general support for self-control theory with strong limitations based on convenience samples with non-response bias and honesty of responses (Donner et al., 2016a).

More recent literature expands on self-control theory to determine additional explanations of police misconduct. Other criminologists have yielded similar findings to Donner and his colleagues. Zavala and Kurtz found support for self-control theory as it applies to problematic alcohol consumption by police officers (2017). A study examining effective parenting, development of self-control, and "code of silence" adherence found general support for self-control theory with caveats of additional predictive factors (Donner et al., 2020). Based on a multi-agency sample of police supervisors, Donner found prior misconduct had stronger predictive utility compared to their measure of low self-control when predicting future likelihood of workplace deviance (2019). This conclusion echoes earlier claims of general support for self-control theory while not ruling out additional explanations from other criminological theories (Donner & Jennings, 2014).

In an early test of self-control theory, researchers conjecture that this theory may explain the gendered difference in offending (LaGrange & Silverman, 1999). Criminologists have acknowledged there may be gendered explanations of police crime, (see Gaub, 2020; Gaub & Holtfreter, 2022) but have yet to examine this perspective through a self-control lens.

Strain theory

Strain theory is built on the underlying assumption that strain is the root cause of criminal behavior. Strain can arise from the failure to achieve positively valued goals, removal of positive stimuli, or the introduction of negative stimuli (Agnew, 1992). The earliest application of strain theory to police misconduct in the United States was a qualitative examination from two large metropolitan police departments in the South. All of the 32 current and former police officers reported experiencing strain associated with their careers and duty assignments (Arter, 2007). This researcher identified six stressor categories (administrative stressors, criminal justice system stressors, experiential stressors, undercover stressors, family stressors, and social stressors), all of which were associated with police misconduct (Arter, 2007). This study concluded by calling for a larger replication of their study to improve the validity of their results (Arter, 2007). Although this study has not been replicated, their findings served as a foundation of understanding for more recent empirical applications of strain theory to police misconduct.

Criminologists have recognized the importance of examining a multitude of different stressors that could correlate with police misconduct. In a study of Baltimore police, researchers examined how an officer's prior strain, such as childhood abuse and interparental violence, might influence aggression and stress responses associated with work in law enforcement (Kurtz et al., 2015). They concluded that prior strain, as well as work-related strain, influences the stress and aggression responses by law enforcement officers (Kurtz et al., 2015). Researchers posit similar findings about work-related strain. Harris conjectures that the experiences officers face on the job can erode their morals and lead to problem behaviors (2009). Bishopp and colleagues explain that organizational stress associated with policing influences the misconduct committed by officers (2016). Furthermore, researchers found that specific stressors were associated with specific acts of misconduct. Fatigue and internal investigations were significantly associated with driving misconduct, while the stress of court appearances was significantly associated with the use of unnecessary force (Bishopp et al., 2016). Although they did not hypothesize reasons for these unique differences, it should be noted that different working environments or neighborhoods might influence the strain experienced by officers and how it might manifest into misconduct. The following section further explores the idea of strain unique to the law enforcement profession.

Occupational and cultural level frameworks

Throughout the theoretical literature about police crime, there exists an exploration of factors unique to American policing. These distinct factors inform theoretical frameworks specific to police crime in America. The following section explores the factors of the profession that may in part explain deviant or criminal behaviors of law enforcement officers.

Police subculture

Studies of the culture surrounding American policing provide insights to the social environment that may foster misconduct and crime. A longitudinal, ethnographic study of an urban police department found that the socialization among officers throughout their introductory months and years are crucial for establishing the informal culture with fellow officers (Van Maanen, 1973, 1975). Stressing the importance of themselves as "outsiders" and adhering to a brotherhood promotes a unique subculture (Van Maanen, 1973, p. 408). Independent commissions have identified similar problematic cultures (see Pennsylvania's Crime Commission, 1974; Report of the Independent Commission on the Los Angeles Police Department, 1991) and us-versus-them mentalities (see Commission to Investigate Allegations of Police Corruption and the Anti-Corruption Procedures of the Police Department, 1994). Through an examination of observational studies, scholars have found that organizational attributes affect the occurrence of police misconduct (King, 2009). The us-versus-them mentality serves as a good basis for the application of learning and control theories.

The processes of police socialization, learning, and control are rooted in the us-versus-them mentality. Police socialization occurs throughout an officer's initial years and often leads to a changed occupational worldview (Stinson, 2020). As the officers gain experience and exposure throughout the job, they begin to distrust anyone outside of the profession (Stinson, 2020). Socialization and adherence to the police subculture may be associated with aggression and cynicism (Stinson, 2020). Police officers learn ways to rationalize their misconduct through the social learning process or through the social control from fellow officers (Kappeler et al., 1998; Quispe-Torreblanca & Stewart, 2019; Stinson, 2020). Techniques of neutralization are learned through socialization to justify their misconduct and violence (see Sykes & Matza, 1957). This process inevitably teaches young, new officers "how to survive on the job" and builds a bond between police peers (Stinson, 2020, p. 77). Officers might *deny responsibility* because the citizens are being provocateurs by breaking the law or *condemn the condemners* by shifting the focus to why would citizens question their authority or discretion (Stinson, 2020). Police officers can *deny injuries* by claiming they did not cause harm and the incident should not be of the public's concern (Stinson, 2020). These learned justifications can reinforce the us-versus-them mentality among police officers.

The police subculture creates a bond and social control between police colleagues. These social relationships may actually create a sense of social cohesion among officers (Donner et al., 2018; Fridell et al., 2021). The us-versus-them mentality evolves to protect the insiders. These attachments to fellow police officers form a "code of silence" among officers.

Adherence to the "code of silence" occurs when police officers fail to report colleagues' misconduct or corruption. The reasons why officers may adhere to this code is multidimensional (Donner et al., 2020). Control theorists suggest a lack of self-control may partly explain an officer's adherence and failure to report deviant behaviors (Donner et al., 2018). Deterrent theorists suggest that the current systems of reporting and discipline lack the ability to control police behavior because punishments are not certain, severe, and swift (Harris & Worden, 2014). Historically, honest police officers have not been able to break the social cohesion among corrupt cops (Commission to Investigate Allegations of Police Corruption and the Anti-Corruption Procedures of the Police Department, 1994). The lack of reporting and strong adherence to the code of silence has only reinforced the deviant police subculture.

Police careers

Examining police misconduct through a life course perspective allows criminologists to reveal new patterns and findings. The life course perspective can be applied to many different types of crime and posits that a longitudinal examination of an individual's stage of life and life circumstances would affect their criminal and deviant behaviors (Elder, 1998). Harris suggests that this theoretical perspective could be applied specifically to police crime by examining the lengths of police careers and the timing of misconduct (Harris, 2009). A longitudinal study concluded that the less experienced police officers are often "hungry" to prove themselves and control crime (Harris, 2009). These officers often initiate more citizen contact and may overreact to perceived threatening behaviors in comparison to more seasoned police officers (Harris, 2009). Examining the trajectories of police careers led Harris to conclude that there are multiple avenues officers can take to the onset of their misconduct (Harris, 2010). The reason they first engage in misconduct may be entirely different than the reason they continue (Harris, 2014). Researchers found that late-stage police crime is quite prominent and may be distinct from earlier forms of misconduct (Stinson et al., 2010). The continued monitoring of police behaviors and the acknowledgement of those behaviors may change over time and experience is of the utmost importance in identifying police misconduct (Harris, 2016). The accumulation of exposure and experience to police work may present individuals with unique stressors through their police careers.

Police strain

Criminologists have acknowledged that police officers experience several different sources of strain. These include low salaries and minimal benefits, psychological burnout, constant exposure to violence and negative stimuli, workplace expectations, and stress associated with the criminal legal system (Stinson, 2020). Many of these stressors are unique to police officers and criminologists have theorized how this might influence their likelihood to commit criminal or deviant acts.

Strain theorists examine how environments or neighborhood characteristics might influence an officer's level of strain. To examine how this unique stressor might influence an officer's behavior, researchers attempted to conceptualize and measure an environmental strain variable. This variable was heavily focused on experiences unique to the occupation. This measure captured items such as responding to a call involving a child's death, felonious assault to self or coworker, and having witnessed a death of a citizen (Bishopp et al., 2019). This measure is meant to capture the surrounding environmental strain that officers often experience. This study concluded that environmental strain was a significant predictor of officers' anger, but was not significant for predicting depression or burnout (Bishopp et al., 2019). Granted this study does not specifically predict the officer's actions or behaviors, it still contributes to the body of literature which could ultimately improve policing policies and practices.

The nature of policing exposes officers to types of strain that are not experienced by most occupations (Kurtz et al., 2015). Law enforcement officers are faced with their own aggression, stress, boredom, and burnout while still engaging with the general public who are often not too fond of encountering law enforcement. They are faced with high levels of distrust and scrutiny (Bishopp et al., 2020). This myriad of factors is not isolated, but rather an accumulation of stressful circumstances throughout their career based on individual, situational, environmental, and organizational factors (Bishopp et al., 2020). Research has suggested long ago that discretionary police behaviors are influenced by individual encounters, but also by the characteristics of the neighborhood (Smith, 1986). This leads criminologists to many unanswered questions about how individual level factors may coexist with structural level environments to influence police behaviors. Theory is the basis for how researchers can enhance our understandings of behaviors. Without thorough theoretical perspectives through both micro and macro lenses, researchers cannot assist in the advancements in empirical-based policies and practices.

Structural level theories

The literature exploring police crime through a structural level perspective is quite scarce. Beyond that, very few studies have been able to produce quantitative findings exploring police crime at a macro level. Scholars suggest the dearth of literature is likely due to the lack of data while still maintaining the significance and importance of needing to enhance our understanding through a multilevel approach (Donner et al., 2021). This remains a strong limitation in many individual level examinations of police crime and misconduct. Structural level criminological theories could inform how an officer's environment, community, and neighborhood would impact their behaviors and actions. If supported, these macro level theories would present an entirely new perspective on how police agencies and policy makers could approach reducing police misconduct and crime.

Conflict theory

The decades surrounding the civil rights movement brought a lot of unrest to communities. During this time, many Americans felt disenchanted with societal values (Stinson, 2020) and criminologists were seeking explanations for crime and misconduct. Conflict theory was growing in popularity throughout these decades. Conflict theory explains that conflict is natural and expected, but the study of how individuals and communities handle conflict is quite telling (Bartos & Wehr, 2002).

The root of this theory lies in power and control. Power can be obtained by having control over various important societal resources, such as wealth or income. Conflict is caused by efforts to control these resources (Lersch, 1998; Stinson, 2020). These concepts ultimately mark societal groups as "haves" and "have nots" (Lersch, 1998). It should be noted that law enforcement officers faced particularly unique experiences during the civil rights movement. Police officers were placed in challenging situations, being expected to maintain order throughout protests and uprisings (Albrecht, 2017, p. 9). According to conflict theorists, police were agents of control and focused on surveillance, manipulation, and coercion during this time rather than crime prevention (Fielding, 1991).

When applying conflict theory to police crime, theorists are concerned with the power and control relationships between police officers and the citizens they are meant to protect and serve. To the best of my knowledge, there is one *quantitative* application of conflict theory explaining police misconduct. Lersch used data from the internal affairs office of one large southeastern police department in the United States over a three year period (1998). She hypothesized that minority groups would be victims of more serious acts of police misconduct, and in turn, file more complaints against officers (Lersch, 1998). This hypothesis was based on the dynamic of minority groups having less power and control of societal resources while police maintain greater power and control. The data ultimately supported this hypothesis (Lersch, 1998). These findings would suggest that police officers are indeed agents of control and might use forms of misconduct to remain dominant in society (Lersch, 1998). She concludes her study by recognizing that macro level theories would not provide a complete explanation for police misconduct (Lersch, 1998). A complete explanation of police crime and misconduct is not likely to come from one theoretical perspective, but rather an accumulation of individual, cultural, and structural factors.

Social disorganization theory

Social disorganization theory explains how united communities can resist crime. Shaw and McKay first explained this theory by stating that delinquency is explained more by the community than the individual (1942). Communities with large proportions of their population having a stake in conformity are less likely to experience high rates of criminal and deviant behavior (Jackson, 1957). These types of community-based theories would suggest that it is the "kinds of places" that can explain crime rather than the "kinds of people" (Stark, 1987). Neighborhoods and communities are confronted with a "complex social phenomenon" (Sampson, 2012, p. 55). The complexities of these communities may serve as a protective or predictive factor of crime. Characteristics of socially disorganized communities are the precursors to weaken social control (Shaw & McKay, 1942). Consequentially, the weakened control within a community leads to the inability of the community to resist crime. Sampson and colleagues coined the idea of *collective efficacy* as an underlying social mechanism of social disorganization. It can be defined as "social cohesion among neighbors combined with their willingness to intervene on behalf of the common good" (Sampson et al., 1997).

Social disorganization theory has been widely applied throughout criminological research over several decades. The tenets of social disorganization theory allow researchers to recognize the "good" and "bad" communities based on the non-random distribution of crime (Kubrin, 2009). The initial studies of patterns of social disorganization were focused on the urbanization, industrialization, and immigration of communities (Shaw & McKay, 1942; also see Park & Burgess, 1925). More recent studies have expanded this exploration to examine collective efficacy, social control, and other subsequent elements of the theory (see Kubrin, 2009; Sampson, 2012; Sampson et al., 1997; Yesberg et al., 2023). Criminologists have continued to apply social disorganization theory to studies of urbanization (Goodson & Bouffard, 2020), neighborhood disadvantage (Lei & Beach, 2020), geographic distribution of intimate partner violence (McDowell & Reinhard, 2023), substance use and abuse (Confer et al., 2023), and a variety of other criminological topics (also see Sampson, 2012; Sampson & Groves, 1989). The continued application of this theory proves its importance and relevance to criminological literature.

Applying social disorganization theory to police misconduct and crime offers an alternative perspective of examining police behaviors. While there exists an abundance of studies exploring how an officer's individual characteristics influence their behavior, very few studies examine the effects of their neighborhood context on their behavior or social disorganization markers on variables. Smith published one of the few empirical studies applying neighborhood-level factors to police behaviors (1986). His study was based on the premise that "police patrol both people and places" (Smith, 1986, p. 337). He recognized that police have vast discretion in their daily contacts with citizens and places they patrol. He hypothesized that the discretionary behaviors of police would change throughout differing neighborhood contexts (Smith, 1986). He ultimately found support for this hypothesis and concludes that “police behave different in different neighborhoods” (Smith, 1986, p. 339). Though this study did not explicitly study corrupt or deviant behaviors of police, it provides general support to the ideal that a police officer’s actions are in fact partly determined by the neighborhood in which they police.

Kane continued the exploration of studying police behaviors through a macro level lens. He examined how the social ecology of police crime could be explored through both social disorganization and conflict theories. He hypothesized that the social disorganization of neighborhoods may create an environment for police misconduct because, “(1) residents may not have in place the social networks necessary to organize against police malpractice, and (2) communities characterized by urban distress often experience high levels of police-citizen conflict due to lapses in police legitimacy” (Kane, 2002, p. 868). Using two decades of data from New York City police precincts and divisions, Kane found support for the idea of a social ecology influencing patterns of police misconduct (Kane, 2002). He specifically concluded that structural disadvantage, population mobility, and increases in the proportion of Latino population increased police misconduct (Kane, 2002). These findings were explained by the lack of informal social control mechanisms necessary to curb conflict with the neighborhood, hence encouraging police misconduct. Smith’s previous study exploring police discretionary behaviors produced similar results about the discretionary nature of coercive authority. Coercive authority by police was positively correlated with neighborhood instability, racial heterogeneity, lower socioeconomic statuses, and proportions of single parent households (Smith, 1986).

Two more recent studies have provided additional support for social disorganization theory when applied to police behaviors. A study using data from New York City Police Department found indicators of social disorganization are associated with coercive action by police officers (Martin & Kaminski, 2021). Using four years of data from the Dallas Police Department, another study concluded that social disorganization variables helped explain patterns of police-decision making associated with arrest trajectories (Wong & Worrall, 2023). Coupled with Kane's results, these studies found overall support for social disorganization theory as it applies to police crime; however, these studies are not without limitations.

Each of the current studies using macro level theoretical perspectives about police crime are strongly limited by the data they used. To my knowledge, there exist no known *quantitative* studies examining police misconduct through a structural level lens on a national scale. Each study has been limited by examining at most three cities (see Smith, 1986). Criminology on a structural level provides vast insights to patterns of national problems, such as police corruption and misconduct. Beyond individual level perspectives, these theories can provide policy makers and police leaders with a new perspective on how to decrease police misconduct and crime.

CHAPTER III. CURRENT STUDY

Building on a rich history of research and keen public interest in the topic of police crime, the purpose of this dissertation is to advance the macro level understanding of police crime through an application of social disorganization theory to American counties. Using a combination of five nationwide datasets (the Henry A. Wallace Police Crime Database, the UCR, the ACS, the CSLLEA, and the United States Department of Agriculture), three primary research questions are investigated. The first research question asks what are the significant county level correlates of police crime (RQ1)? Based on social disorganization theory, I hypothesize that measures of social disorganization will be significantly associated with the measure of police crime (H1). If this hypothesis is supported, counties throughout the United States with higher levels of social disorganization would have higher counts of police crime.

The second research question asks whether the significant correlates of general crime are the same for police crime at a structural level (RQ2). I hypothesize that I find support for social disorganization theory and the measures of social disorganization have a significant relationship with general crime (H2). I expect that the counties throughout the United States with values indicating higher levels of social disorganization will be associated with higher counts of general crime.

The third and final research question investigates if there is a significant relationship between general crime and police crime at a structural level (RQ3). This research question explores the potentially complex relationship between general crime and police crime. I hypothesize that there will be a significant relationship between general crime and police crime (H3). If this hypothesis is supported, I expect to see the counties with higher counts of general crime also having higher counts of police crime.

These research questions and hypotheses guide the longitudinal, county level analyses of three analytical chapters. In Chapter V, I regress a longitudinal, county level measure of police crime on predictors using a series of mixed-effects regression models. In Chapter VI, I use similar models to regress a longitudinal, county level measure of general crime onto predictors. A comparison of these models to the previous chapter's models determines similarities and differences among significant predictors for general crime compared to police crime. Lastly, in Chapter VII, I use a similar analytical approach to the prior two chapters. Mixed-effects models regress a longitudinal, county level measure of police crime onto predictors. A focal independent variable of lagged general crime is included. A model building process explores how specific types of general crime may predict police crime. Additionally, mixed-effects models which regress general crime onto a lagged police crime variables and predictors are explored. This final analytical chapter further explores the complex relationship between general crime and police crime. Each analytical chapter commences with a discussion about the specific analytical approach, data structure, and descriptive statistics of the data. The findings from these mixed-effects models inform a final discussion chapter about the complex relationship between general crime, police crime, and structural characteristics, including measures of social disorganization. This chapter offers support or opposition for the hypotheses. These results advance the understanding of police crime from a structural perspective and inform evidence-based policy aimed at reducing police crime throughout the United States. The goal of this dissertation is to improve American policing through these policy recommendations.

CHAPTER IV. DATA AND MEASURES

The research questions of this study inquire about a structural level understanding of police crime and its relationship with general crime. The currently available research does a thorough job of exploring police crime from an individual level perspective (e.g. Bishopp et al., 2016, 2020; Chappell & Piquero, 2004, 2004; Donner, 2013; Donner et al., 2018, 2021; Stinson, 2020). These studies have informed discussions about individual factors that may be associated with criminal behaviors of police officers but fail to explore police crime from a more macro level. This dissertation advances the understanding of police crime using a nationwide, longitudinal, county level, panel dataset.

At the time of this study, to my knowledge, there exist no known quantitative studies examining police crime through a structural perspective on a national scale. Furthermore, to my knowledge, there existed no known dataset capable of exploring police crime throughout the United States at a structural level over time at the inception of this study. This study merges five nationwide datasets by county-years to advance the understanding of police crime. Data are pieced together from multiple sources to provide a way forward to explore an otherwise unknown phenomenon within criminological research and police crime policy.

The development of this longitudinal, nationwide panel dataset has the ability to inform policy throughout the United States based on county level characteristics. Prior studies were limited by their data and their inability to span across time and location. Information from the Henry A. Wallace Police Crime Database provides a measure of police crime throughout the United States, aggregated by county-year. This will be the first measure of police crime, to my knowledge, with the ability to capture data spanning American counties over a five-year period.

The longitudinal, panel data provides a measure of police crime for each American county over the years 2013-2017.

Additional information is combined from four other datasets to explore the research questions for this study. Each dataset provides a unique perspective on the structural level characteristics of American counties. Data from the UCR allows for the exploration of the relationship between police crime and general crime. Information from the ACS offers the ability to test whether social disorganization theory can be associated with police crime. Additional variables are pulled from the ACS. The CSLLEA provides the ability to control for law enforcement presence in counties throughout the United States and determines the coverage bias of the crime reported to the UCR. Information from the United States Department of Agriculture is included as a control measure. These datasets each uniquely provide insight to the investigation of police crime throughout the United States.

These data are merged to create a large dataset describing American counties over a five-year period. Years are nested within counties, allowing for the ability to describe counties over time. The construction of this dataset creates a large panel dataset formatted in a long file. In other words, each row of data indicates a specific county during a specific study year. Each county has up to five rows of data, indicating five years of data. Despite the complexities of these data, the format of this newly constructed dataset is not dissimilar to other preexisting longitudinal panel datasets. This allows for a relatively straightforward analysis of these data. The data management, manipulation, and merging are conducted using the R programming language 4.2.2 (R Core Team, 2023) with RStudio's integrated development environment 2023.06.1+524 (RStudio Team, 2023). Packages used throughout the data preparation and analysis are listed in Appendix A. Additionally, data management and analyses are conducted using Stata/SE 15.1 (*Stata/SE: Statistical Software*, 2017). More information about managing and analyzing long panel data can be found in literature (see Rabe-Hesketh & Skrondal, 2012).

Data

Henry A. Wallace Police Crime Database

The Henry A. Wallace Police Crime Database contains summary information about criminal arrest cases of non-federal sworn law enforcement officers in the United States since 2005. The Police Integrity Research Group at Bowling Green State University collects, maintains, and disseminates these summary data to the public through their database. A publicly available succinct dataset is not available at the time of this project, but the principal investigator of the Police Integrity Research Group graciously provided the raw data for this dissertation. Due to the lack of official data pertaining to arrested law enforcement officers, the research group employs unique methodology to identify and track information about these criminal arrest cases.

Local, regional, and national news agencies report on the arrests of law enforcement officers as it is shocking when someone who is sworn to uphold the law finds themselves on the other side of it. Google News maintains an aggregator of news articles from thousands of publishers across the country (Vise & Malseed, 2005). The Police Integrity Research Group monitors several dozen Google Alerts which constantly crawl the Google News publications for key words relating to the arrest of a law enforcement officer. Search terms such as "officer arrested" and "police officer indicted" identify Google News articles that may pertain to a non-federal sworn law enforcement officer being criminally arrested.

The research team captures all news articles from these Google Alerts and confirms whether each case meets the inclusion criteria. These criteria include (1) the arrested individual being a non-federal sworn law enforcement officer in the United States at the time of the arrest and/or the commission of the crime, (2) the arrest occurring on or after January 1, 2005, in the United States. The county location of the arrested officer's place of employment is documented for each criminal arrest case using a county identifier. Further information about the county identifier is discussed in the *Structure of Data* section in this chapter.

This distinct methodology has been found to effectively track the arrests of law enforcement officers throughout the United States (Payne, 2013). The Henry A. Wallace Police Crime Database has found over 1,000 criminal cases of arrested non-federal law enforcement officers in the United States each year since 2008. Content analysis is conducted on publicly available news articles, videos, court records, and more to capture information on over 270 variables. Due to the scope of this project examining police crime at a structural level, these data were collapsed by county-years to develop a count of criminal arrest cases for each county during each year of study, 2013-2017. Vast amounts of information pertaining to each criminal arrest case are lost by this method, yet the aim of this project is not focused on individual level police crime. Prior research has used the full range of variables to gain insights on police sexual violence, off-duty police crime, racial disparities in police violence, officer involved domestic violence, police officers arrested for drunk driving, and more (see Stinson et al., 2012, 2014, 2015, 2021; Stinson & Liederbach, 2013). Additional information, summary data, and more in-depth methodology can be found on the Henry A. Wallace Police Crime Database's website (see Stinson, 2023). This methodology has been found to be exempt by the Human Subject Review Board (HSRB) at Bowling Green State University due to the research methodology not involving human subjects as defined by the federal regulations.

This study defines *police crime* as criminal arrest cases of non-federal sworn law enforcement officers. This definition is limited to behaviors that have been detected and for which probable cause has been established. This provides a level of objectivity when classifying criminal behaviors, but fails to capture non-criminal, corrupt behaviors. The criminal behavior could have been committed on- or off-duty, as long as the individual was employed as a sworn officer at the time of crime or at the time of arrest. This variable aims to capture the phenomenon of criminal behaviors committed by police officers throughout the United States.

Although these data provide a longitudinal, nationwide measure of police crime throughout the United States, they are not without limitations. First, the methodology strictly captures the criminal arrests of non-federal sworn law enforcement officers. This fails to capture non-criminal police misconduct or criminal misconduct which may not result in an arrest or prosecution. Second, this measure of police crime is reliant on publicly available news coverage of the criminal arrest cases of sworn law enforcement officers. There may be cases of police crime that are not captured due to the discretion of media organizations. These limitations may produce a selection bias in these data. I return to these limitations in the final chapter of the dissertation with respect to the overall findings and policy implications of this study.

Uniform Crime Reporting Program

The United States Federal Bureau of Investigation (FBI) has maintained the UCR for nearly a century. This report has provided the public with crime statistics throughout the United States since 1930 (*Crime/Law Enforcement Stats (Uniform Crime Reporting Program)*, n.d.). Agencies choose to voluntarily submit their crime data through their state programs or directly to the federal program (Federal Bureau of Investigation Crime Data Explorer, 2022). The FBI maintains and aggregates these data by reporting agencies. These data are publicly available for exploration through the Crime Data Explorer (see Federal Bureau of Investigation Crime Data Explorer, 2022) or publicly available for download from the Inter-University Consortium for

Political and Social Research (ICPSR) which is maintained by the Institute for Social Research at the University of Michigan (see Inter-University Consortium for Political and Social Research, 2023). The ICPSR also provides a crosswalk which was applied to merge each agencies' FIPS code to these data (see United States. Bureau Of Justice Statistics, 2015). A further discussion of FIPS codes is provided in the *Structure of Data* section of this dissertation. Many law enforcement agencies opted out of reporting to the UCR due to the voluntary nature of the program. The UCR maintains reporting from more than 18,000 city, county, state, special, or federal agencies throughout the United States (*Crime/Law Enforcement Stats (Uniform Crime Reporting Program)*, n.d.). The coverage of the UCR remains higher than any other available national measures of crime for this study's years.

The UCR captures a count of each criminal offense reported by agencies. These offenses range from non-violent misdemeanors such as petty theft and drunkenness to felony-level murder and sexual battery. Many researchers use only select crimes from the UCR to develop a measure of index crimes (see Baumer et al., 2018; Lauritsen, 2023; Weisburd, 2015). I use the full range of offenses included in the UCR. This operationalization of the UCR data provides my study with the most comparable measure between general crime and police crime. My measures of both general crime and police crime include a full range of criminal behavior. A further discussion of the included offenses is within the *Measures* section of this chapter.

When reporting crime data to the FBI, each agency has the ability to report these offenses, which are then aggregated by month to produce a monthly count for each offense, for each reporting agency. These data are then made publicly available by year. For the purpose of this study, each count of offenses is totaled to provide an overall count of crime. These data are aggregated by county to produce a county level measurement of crime over time.

Not all law enforcement agencies report their arrests to the UCR due to the voluntary nature of the data collection. As such, there is a selection bias in these data. To combat this bias, a count of agencies that reported data is captured for each county-year within this study. This count is constructed by counting each unique agency identifier within the data for each county-year. This measure is used to determine the percentage of agencies that reported data for each county-year. A further discussion of this is included in the *Measures* section of this chapter.

American Community Survey

The ACS is administered to a sample of households throughout the United States each year. The sample of households over a five-year period are used to construct a county level estimate. Each county in the United States is represented in the sampling design, meaning each five-year cycle has one set of estimates per American county. Five-year cycles of the ACS are representative of the entire United States population. This dissertation uses one dataset of five-year estimates. These data span the years of 2008 through 2012 with each county being sampled exactly once.

The survey captures a wide variety of information pertaining to the individuals within the household and the communities in which they live. These data provide proxy measures of the social disorganization of a county in a given year. These measures include information about the income inequality and distribution, employment and insurance statuses, compositions of households and housing units, and the average educational attainment. These measures ultimately provide insight as to the level of social disorganization of a county. Each measure is first explored as an individual item and later is constructed into a scale for multivariate analysis.

Additional variables from the ACS are included in this study as control measures. These variables include information about the counties' demographic makeup of sex and age, as well as the percent of individuals within a county who were identified as White. The total population of the county is also used as a control measure throughout the study.

Census of State and Local Law Enforcement Agencies

The Bureau of Justice Statistics maintains the CSLLEA (see United States Department Of Justice. Office Of Justice Programs. Bureau Of Justice Statistics, 2011). This census captures agencies that employ one or more sworn officers. The data collection instrument was physically mailed to agencies nationwide. Data from this census contain information about department size, type of agency, number of full- and part-time employees, estimated budgets, and more departmental factors. Individual officer information is not provided by agencies. This dissertation used data from the 2008 implementation of the CSLLEA.

The data included in the CSLLEA is used for two purposes throughout this dissertation. First, counts of officers and agencies within a county capture the overall presence of law enforcement. Second, the counts of agencies in a county are used to determine the coverage of the UCR data. As previously discussed, the UCR is voluntary so not all agencies are expected to report their crime data, which would result in a coverage and selection bias. From the UCR data, a count of agencies that reported data is captured. The count of agencies that reported data to the UCR is compared to the count of total law enforcement agencies as reported by the CSLLEA. A comparison of these measures captures the proportion of agencies that reported to the UCR for each county. A further discussion of this constructed measure is included in the *Measures* section of this chapter.

Despite the usefulness of these data, these data are not without limitations. The variables captured in the CSLLEA are needed to explore the research question within this study, however the 2008 wave is the only available wave during the study's timeframe. Due to the historical context during this time, many police agencies were experiencing layoffs and an overall lower number of employees (The Impact of the Economic Downturn on American Policing Agencies, 2011). This would cause an underestimate for count of officers throughout the remaining years of data. This underestimate remains consistent throughout the study and should be taken into consideration when examining the results related to these data. The CSLLEA attempted data collection in years 2012 and 2014 but the data were not operational. Summary information was released for the 2018 wave of the CSLLEA, but the data are not yet publicly available at the time of this study.

United States Department of Agriculture – Economic Research Service

The United States Department of Agriculture maintains a classification structure for counties and independent cities, which designates levels along a rural-urban continuum code. The Economic Research Service distinguishes counties by population size, urbanization, and proximity to metropolitan areas (*Rural-Urban Continuum Codes*, 2013). This methodology provides a more detailed approach to the binary classification structure, metropolitan and nonmetropolitan, previously used by the Office of Management and Budget. This binary structure is subdivided into three metropolitan and six nonmetropolitan groupings, resulting in a nine-point continuum code measuring rurality. This dissertation uses the 2013 rural-urban continuum codes. Although these codes were first published in February 2013, the methodology used to categorize these codes use data from the 2010 Census and the 2010 ACS five-year cycle (*Rural-Urban Continuum Codes*, 2013). Therefore, there should be no concerns of time-order during the multivariate analysis.

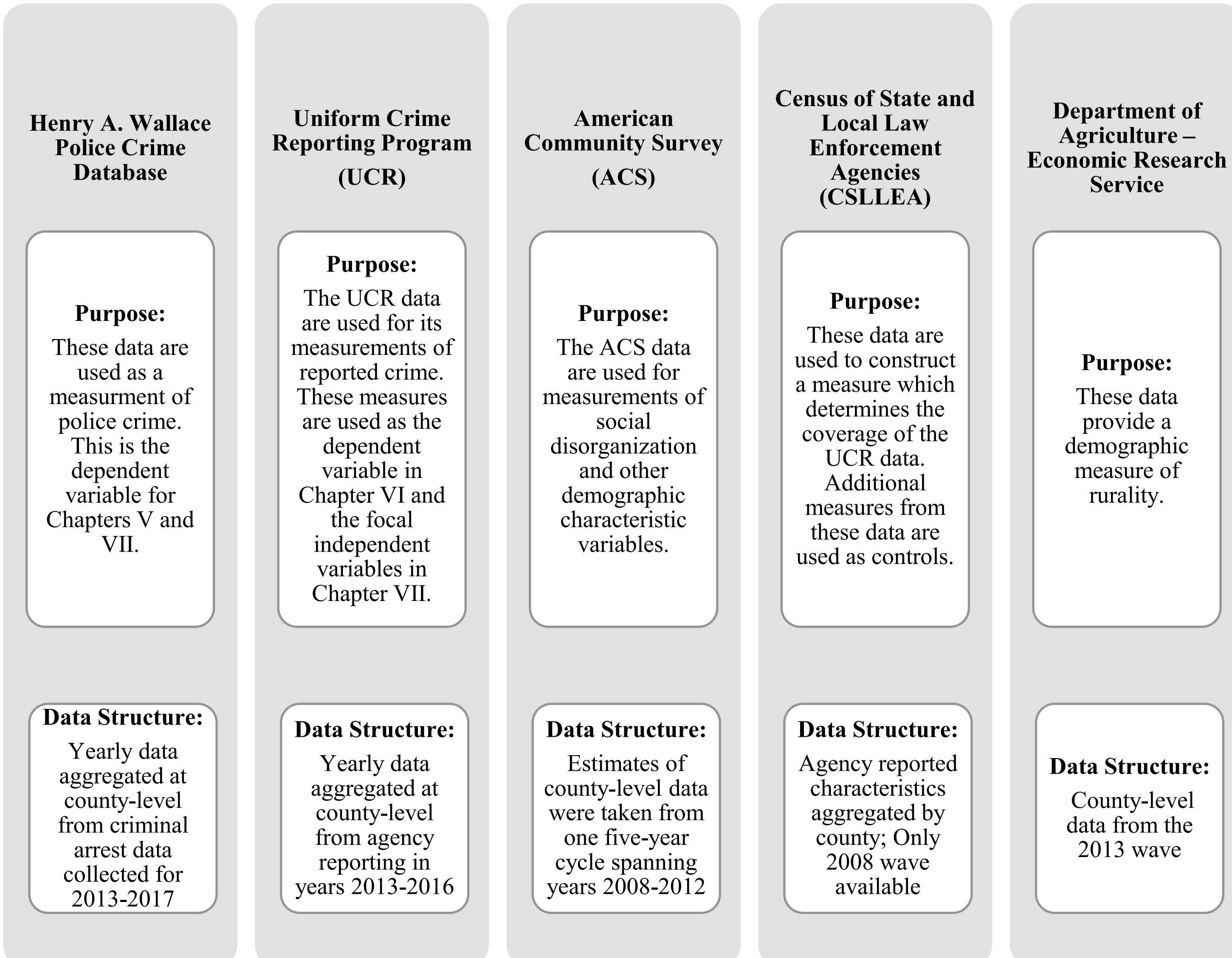
The nine-point continuum code ranges from the most urban counties in the United States to the most rural. Counties identified as the most urban are within a metropolitan area with a population of over one million. The counties identified as the most rural are not adjacent to any metropolitan areas and have an urban population less than 2,500 (*Rural-Urban Continuum Codes*, 2013). This measure of rurality is intended to serve as a control measure throughout this dissertation.

Structure of Data

Each dataset serves a unique purpose throughout this study and the construction of this newly merged dataset was done with intention and precision. The inclusion of data from the Henry A. Wallace Police Crime Database provides this study with a longitudinal, county level measure of police crime. The addition of the UCR data allows for a comparison between police crime and general crime, as well as an investigation into the relationship between general crime and police crime. Data from the ACS grants the ability to apply social disorganization theory, and also, provides control measures. Variables from the CSLLEA and the Department of Agriculture are intended to limit the noise within the models by acting as control measures. Data from the CSLLEA are also used to construct a measure of coverage for the UCR. Figure 1 displays the explicit purpose of each dataset.

Each individual dataset is thoroughly examined to determine the detailed structure of the data prior to the merge. Criminal arrest case information from the Henry A. Wallace Police Crime Database is aggregated by county-years to construct longitudinal, panel data for years 2013-2017. The agency-level data from the UCR are also aggregated by county-year for years 2013-2016. Time-invariant measures are gathered from the ACS, CSLLEA, and the Department of Agriculture. One five-year cycle of the ACS is used to gather county level estimates for variables at one time point spanning the years 2008-2012. The CSLLEA data are aggregated by

Figure 1. Structure and Purpose of Data



county to provide time-invariant measurements. Figure 1 also displays the unique structure of each data set.

The data for this project are merged by joining year and county indicator variables to construct a longitudinal, county level, panel dataset. An identifier from the National Institute of Standards and Technology identifies county or county level equivalents. Codes from their Federal Information Processing Standards (FIPS) Publication 6-4 (Federal Information Processing Standards Publication 6-4, 1990) are used to classify counties (or county-equivalents such as independent cities, parishes, or boroughs). This variable is the county indicator used to merge all datasets. The first two digits of the five-digit code are a state indicator. The remaining three digits indicate the county within each state. The full five-digit code uniquely identifies 3,143 counties or county-equivalents throughout the United States (*Substantial Changes to Counties and County Equivalent Entities: 1970-Present*, 2023).

For the multilevel models, time (year) is the first level, which is nested within the second level, counties. This structure allows for insights to be made about both within-county and between-county. The dependent variables in all analytical chapters, as well as the focal independent variables in Chapter VII, are time-varying within counties. The data for this project examines 15,715 county-years though missing values on some variables limits the final analytical sample sizes. A discussion of sample size is provided in each analytical chapter as the models require different samples.

The data used throughout this project allow for a unique opportunity to examine police crime through a macro lens. Although the datasets merged with the police data from the Henry A. Wallace Police Crime Database were all publicly available, these datasets have not been merged into a single piece of infrastructure for use in research to the best of my knowledge. The present data framework provides a rare and valuable opportunity to study police crime from a structural perspective. While the datasets used in this study have been used individually to enhance our understanding of criminal behavior, they have not been aggregated in a way that fully utilizes their capacities in researching crimes committed by police officers. Accordingly, the construction of the dataset used throughout this project promotes a unique, comprehensive, and new methodological approach to research on policing generally and police crime specifically.

Measures

Key variables

Police crime

The Henry A. Wallace Police Crime Database is maintained by the Police Integrity Research Group. This research group defines police crime as "crime committed by nonfederal sworn law enforcement officers who have the general powers of arrest (e.g., police officers, deputy sheriffs, state troopers, etc.)" (Stinson, 2023). It is important to note this operationalization limits this variable to include only criminal behaviors of nonfederal sworn law enforcement officers. This measure does not capture non-criminal police misconduct. Conceptually, this variable captures a wide variety of police crime. This measure is not limited by the duty-status of the police officer, nor does it limit the types of crime that are classified as "police crime." These crimes range from petty misdemeanors to felony offenses. All criminal arrest cases of nonfederal sworn law enforcement officers are captured by this variable, despite the offenses for which they are charged.

As previously discussed, data from the Henry A. Wallace Database are subject to limitations associated with selection bias due to media discretion. This limitation is a standard concern when using news articles for the source of data. Scholars have found that police misconduct reported by news agencies is consistent with the official police records of events (Ready et al., 2008). Furthermore, research suggests that police agencies are not effective at limiting the media's narrative of police misconduct (Chermak et al., 2006). This would suggest that although this limitation is important to discuss, these data may be more reliable and valid than some might assume.

Each row of data provided from the Henry A. Wallace Database represents a criminal arrest case of a police officer, arrested during the study years, 2013-2017. The officer's employing agency is located and the FIPS code is documented. To construct the variable used for this dissertation, I aggregate the data by county-year. This provides a count of police crime for each of the county-years of the study period. It is important to note, a zero value for this variable is meaningful. This indicates that zero criminal arrest cases of police officers have been identified by the Police Integrity Research Group despite the thorough methodology of constantly crawling the Google News search engine.

Figure 2 displays the counts of police crime across American counties throughout the entire study period. This map is largely filled with zero values, indicating zero police crime has been identified in these areas during the study years. The counties with the largest counts of police crime throughout the study years were Los Angeles County (CA) with 137 cases of police crime, followed by Philadelphia County (PA) with 91 cases of police crime and Cook County (IL) with 82 cases of police crime. Population size will be used as a demographic characteristic variable throughout multivariate analysis but is not accounted for within this map.

Table 1 displays descriptive statistics for the time-variant measure of police crime. The count of police crime in each county-year ranges from zero to 42.000 criminal arrests cases, with

Figure 2. Map of Identified Police Crime throughout the United States, 2013-2017.

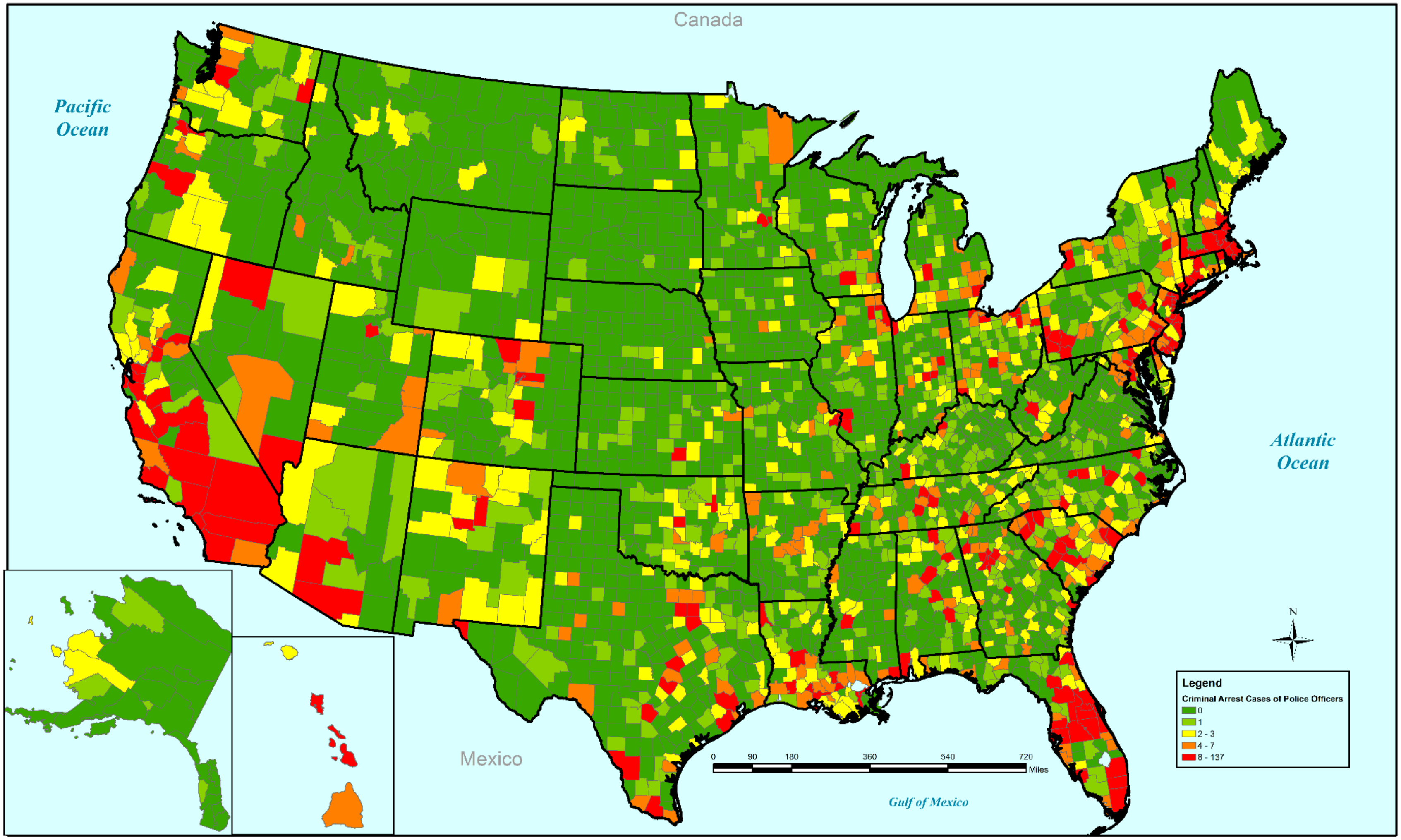


Table 1. Descriptive Characteristics of Variables Used in Analyses.

	Years available	Time-variant or time-invariant	*n* (county-years)	Mean	SD (between)	SD (within)	Range
Key variables							
Police crime	2013-2017	T.V.	15.715	0.400	1.331	0.791	0.000 – 42.000
General crime (UCR)	2013-2016	T.V.	11,532	2,118.730	4,368.267	312.968	0.000 – 120,503.000
Crimes against persons (UCR)	2013-2016	T.V.	11,523	419.848	920.415	64.703	0.000 – 25,747.000
Crimes against property (UCR)	2013-2016	T.V.	11,523	501.960	1,170.186	92.590	0.000 – 35,456.000
Crimes against society (UCR)	2013-2016	T.V.	11,523	1,196.921	2,318.127	187.025	0.000 – 59,705.000
Social disorganization variables							
Gini index	2008-2012	T.I.	3,143	0.435	0.035	---	0.316 – 0.599
Percent below poverty line	2008-2012	T.I.	3,143	16.296	6.437	---	0.000 – 49.500
Percent unemployed	2008-2012	T.I.	3,143	8.580	3.774	---	0.000 – 27.217
Percent uninsured	2008-2012	T.I.	3,413	15.154	5.767	---	2.600 – 66.200
Percent female headed households	2008-2012	T.I.	3,413	6.479	2.458	---	0.000 – 19.297
Percent owner-occupied housing units	2008-2012	T.I.	3,413	72.574	7.952	---	0.000 – 94.725
Percent vacant housing units	2008-2012	T.I.	3,413	17.656	10.444	---	1.960 – 78.788
Percent high school educated	2008-2012	T.I.	3,413	84.144	7.041	---	44.900 – 97.500
Demographic characteristics							
Law enforcement agencies	2008	T.I.	3,133	5.738	7.219	---	1.000 – 135.000
Sworn law enforcement officers	2008	T.I.	3,133	244.241	1,137.909	---	0.000 – 37,503.000
Percent agencies reported (UCR)	2013-2016	T.V.	11,516	96.564	44.199	10.322	0.741 – 500.000
Rurality	2013	T.I.	3,143	5.008	2.709	---	1.000 – 9.000
Total population / 10,000	2008-2012	T.I.	3,143	9.836	31.370	---	0.007 – 984.002
Sex ratio	2008-2012	T.I.	3,143	100.568	12.169	---	73.400 – 325.000
Age-dependency ratio	2008-2012	T.I.	3,143	65.453	10.244	---	6.300 – 115.000
Percent White	2008-2012	T.I.	3,143	83.908	16.663	---	3.110 – 100.000

an average of 0.400 ($SD_{between}$=1.331, SD_{within}=0.791). As displayed on Figure 2 and by the descriptive statistics, this variable appears to be largely positively skewed.

Table 1 additionally presents the descriptive characteristics of the measures used throughout this project. These statistics include the mean, standard deviations, ranges, and other characteristics of each variable. Appendix B further explores these variables with an examination of the correlations among these variables.

General crime (UCR)

This measure of crime is constructed from data from the UCR. The FBI maintains the yearly UCR data which is disseminated by monthly agency reports for specific crimes. Agencies report three criminal offenses per criminal incident, with the first one indicating the most serious offense. These offenses range from non-violent misdemeanors to murder. Each row of data represents the crime counts of one agency for a specific crime type.

The UCR data disseminated by the FBI are aggregated by county-year to construct a count variable of general crime. This measure is not intended to limit the count of crime by the severity or nature of the crime, but rather counts the number of criminal incidents within each county-year. All possible offenses are included within this measure of crime. This measure captures incidents ranging from non-violent misdemeanors to murder. This operationalization of the UCR data allows for the closest comparison to the police crime measure. Conceptually, this measure of crime is all-encompassing.

To construct this variable, each criminal incident is counted once based on the first (which indicates the most serious) offense reported. First, each yearly UCR dataset is aggregated by county. The aggregated county data for each year is then merged together to create a longitudinal, panel measure of general crime. Each row of data in this newly constructed dataset indicates the crime count for a specific county for a specific year. In other words, the dataset is formatted with long data.

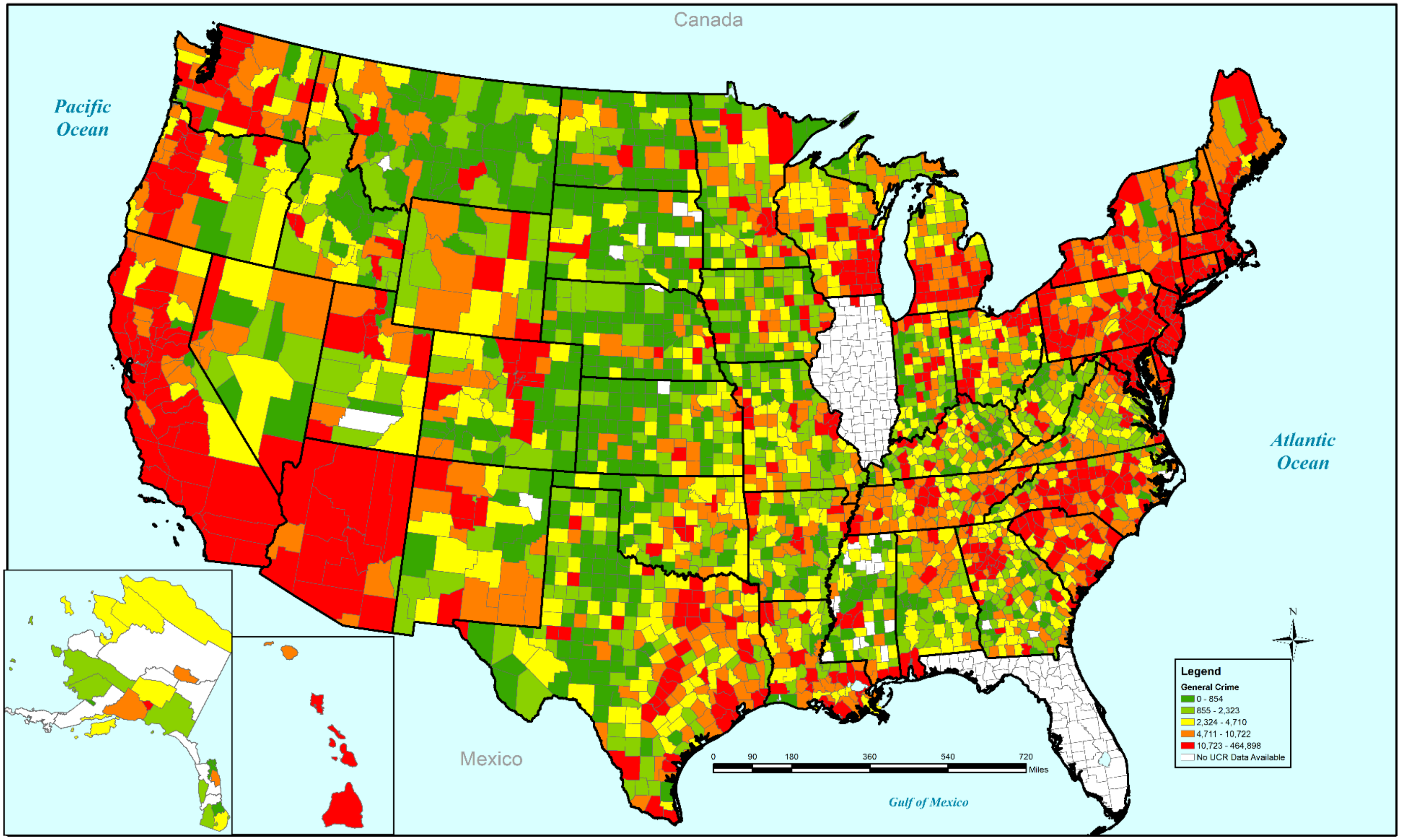
Figure 3 displays a map of the general crime measure throughout the study years, controlling for county population. This map displays a clear lack of reporting from Florida and Illinois agencies, as well as scattered agencies throughout the United States. This represents counties in which all the agencies within the county failed to report data to the FBI for the entirety of the study years. Furthermore, it should be noted that some of these counties may have received reporting from only a small proportion of agencies that serve that county. These counties are excluded from multivariate analysis. Further discussion of this exclusion is include within the *Structure of Data* section within this chapter.

Table 1 displays descriptive statistics for this time-variant measure of general crime. These values range from zero to 120,503.000 crimes with an average of 2,118.730 crimes reported in each county-year ($SD_{between}$=4,368.267, SD_{within}=312.968). This variable is positively skewed with many county-years reporting close to zero crime.

Types of general crime: Crimes against persons, property, or society

The general crime variable constructed from the UCR data is broad and includes a wide variety of criminal offenses. That variable serves the purpose to answer the presented research questions in Chapter VI, but may fail to tell the intricate details of what is occurring between general crime and police crime in Chapter VII. To further explore the relationship between general crime and police crime, I divide the general crime variable into subcategories. When considering which subcategories to explore, I consider many options. The FBI has recently shifted its focus from the UCR to the National Incident Based Reporting System (NIBRS). A further discussion of this can be found in the *Data Considerations* section of this chapter. The NIBRS includes a much

Figure 3. Map of Reported General Crime throughout the United States, 2013-2016.



more detailed report of criminal offenses committed throughout the United States. Within this report, crime is subcategorized by crime against persons, crimes against property, and crimes against society. I found that this categorization scheme offers this project further insights into the relationship between general crime and police crime, as explored in Chapter VII. Furthermore, this classification scheme provides clear guidance and objectivity to the classification of many UCR variables.

The UCR offenses are sorted into three categories: crime against persons, crimes against property, and crimes against society. These categories are curated from the NIBRS classification structure for their offense variables (See *Crimes against Persons, Property, Society*, 2012). Many of these offenses coincide with the NIBRS offenses, so classification is straightforward. The offenses that did not coincide with a NIBRS offense are subjectively classified into one of the three categories based on the patterns witnessed in the NIBRS classification. The NIBRS classification for a robbery offenses is a crime against property because the object of the offense is to obtain money or property (*Crimes against Persons, Property, Society*, 2012). I have subjectively changed this classification to a crime against person due to the UCR definition of robbery including the use (or threat of use) of force or violence against a victim (*Crime in the United States: Robbery*, 2018). Each criminal incident reported to the UCR is categorized into one of these categories, based on the first (which indicates the most serious) offense reported. Table 2 displays a detailed organization of the offenses in these three categories.

The first category, crimes against persons, includes offenses such as, but not limited to, homicide offenses, assault offenses, and sexual assault offenses. This time-variant measure ranges from zero to 25,747.000 crimes reported in each county-year with an average of 419.848 crimes against persons ($SD_{between}$=920.415, SD_{within}=64.703). Zero values of these UCR crime

Table 2. Classification of Offense Variables into Types of Crime.

UCR Offense Variable	Crime Against…	NIBRS Classification or Subjective
Murder and non-negligent manslaughter	Persons	NIBRS Classification
Manslaughter by negligence	Persons	NIBRS Classification
Forcible rape	Persons	NIBRS Classification
Aggravated assault	Persons	NIBRS Classification
Other assaults	Persons	Subjective
Sex offenses (not sexual battery or prostitution)	Persons	Subjective
Offenses against family and children	Persons	Subjective
Robbery	Persons	Subjective
Burglary - breaking or entering	Property	NIBRS Classification
Larceny - theft (not motor vehicles)	Property	NIBRS Classification
Motor vehicle theft	Property	NIBRS Classification
Arson	Property	NIBRS Classification
Forgery and counterfeiting	Property	NIBRS Classification
Fraud	Property	Subjective
Embezzlement	Property	NIBRS Classification
Stolen property – buying, receiving, possessing	Property	NIBRS Classification
Vandalism	Property	NIBRS Classification
Weapons – carrying, possessing, etc.	Society	NIBRS Classification
Prostitution and commercialized vice	Society	NIBRS Classification
Total drug abuse violations	Society	NIBRS Classification
Gambling	Society	NIBRS Classification
Driving under the influence	Society	Subjective
Liquor law violations	Society	Subjective
Drunkenness	Society	Subjective
Disorderly conduct	Society	Subjective
Vagrancy	Society	Subjective
All other non-traffic offenses	Society	Subjective
Suspicion	Society	Subjective

types measure the county-years in which other crime types are reported with valid counts, but there are no criminal incidents classified to this specific type reported for the given county-year.

The second crime type, crimes against property, includes offenses such as, but not limited to, burglary, theft, fraud, and arson. The time-variant measure of crimes against property ranges from zero to 35,456.000 crimes reported in each county-year with an average of 501.960 crimes against property ($SD_{between}$=1,170.186, SD_{within}=92.590).

The third and final time-variant crime type variable, crimes against society, is by far the most common crime type within the UCR reported data. This variable captures offenses such as, but not limited to, weapons offenses, drug offenses, driving under the influence, and prostitution offenses. This measure ranges from zero to 59,705.000 crimes reported in each county-year with an average of 1,196.921 crimes against society ($SD_{between}$=2,318.127, SD_{within}=187.025).

Percent agencies reported

As previously explained, the UCR is voluntary and law enforcement agencies are not required to report their crime data to the FBI who maintain this report. As witnessed in Table 1 and Figure 3, the UCR is largely positively skewed with many county-years reporting close to zero crime. This raises the question whether these counties are experiencing incredibly low rates of crime or if there is simply a lack of reporting.

The UCR has a unique identifier for each law enforcement agency that reports data. When constructing the data for this dissertation, I create an aggregate count of agencies that reported data in each county-year. The number of agencies per county that reported to the UCR within the study years ranges from zero to 121 agencies with an average of 4.850 agencies reporting per county. Looking solely at these data, it is impossible to indicate whether the UCR data sufficiently covers reporting from the majority of agencies within each county-year.

Furthermore, there is no indication of how many agencies failed to report data to the UCR during the study years. This brings up strong concerns with the coverage of the UCR data.

To combat this concern, I examine data from the CSLLEA. The data from the CSLLEA includes a count of law enforcement agencies operating in each county throughout the United States. This count ranges from one to 135, with an average of 5.738 law enforcement agencies operating in each county. This count of agencies operating in each county is compared to the count of agencies that reported data to the UCR.

These variables are compared to get an estimate of proportion of agencies that reported data to the UCR for each county-year. The count of agencies that reported their data to UCR is divided by the total number of law enforcement agencies counted by CSLLEA for each county-year. Although this measure is time-variant, this variable is constructed using a time-invariant count of agencies. It is important to note, this percentage is an estimate due to the invariant nature of the CSLLEA data. It is possible that counties may have law enforcement agencies close down or start up within the study years, causing error within this measure.

This variable measuring the percentage of agencies that reported data to the UCR averages over 95% (see Table 1). This indicates that the coverage of UCR is fairly adequate. There exist some counties with less than 10% of their agencies reporting data to the UCR. In the most extreme scenarios, there exist counties such as Cook County (IL) or Lake County (IL) in which only one law enforcement agency out of 135 or 39, respectively, reported to the UCR. It would be extremely inaccurate to use these counties' data throughout the analysis because these counties would inaccurately appear to have very low rates of crime. Although researchers have discussed the potential coverage biases within the UCR (see Loftin & McDowall, 2010), I am unaware of any other criminologists exploring the coverage issue with the use of the CSLLEA data. Because a standard of practice has not been established for this method, I will be exploring different cutoff points for the percentage of agencies reporting throughout my analyses. This discussion will be explored further in the analytical approach of each analytical chapter of this dissertation.

Measurements of social disorganization

Social disorganization theory posits that delinquency and crime can be explained by characteristics of the community, rather than just characteristics of the individual (Shaw & McKay, 1942). It is the socially disorganized communities that might be more vulnerable to crime. Socially disorganized communities tend to have weakened social control which leads to the inability to resist crime (Shaw & McKay, 1942). This dissertation explores the antecedents of social disorganization at the county level. Using data from the ACS, these measures are used as a proxy for the measures of the county's social disorganization. These measures are meant to capture factors that would prevent the county from resisting crime.

The proxies for social disorganization include measures of income inequality and distribution, employment and insurance statuses, compositions of households and housing units, and the average educational attainment. Conceptually, counties with high rates of income inequality, poverty, unemployment, single parent households, and vacant housing are likely to experience higher rates of social disorganization. These variables theoretically capture the precursors of weakened social control within a county. Similarly, counties with low rates of owner-occupied housing units and low average educational attainment are likely to experience a socially disorganized county with weakened social control.

Gini index

The Gini index measure from the ACS is a measure of dispersion of income intended to measure income inequality. This summary statistic captures how a resource is distributed in a specific population (Farris, 2010). The ACS's Gini index captures the dispersion of income within American counties. A zero value indicates perfect dispersion of income, meaning every individual within the county has an equal amount of income. A value of one would indicate the most extreme inequality, meaning one individual would hold all the income within the given county. Values closer to one indicate counties with high levels of inequality. The values for this variable range from 0.316 to 0.599 with an average of 0.435 ($SD_{between}$=0.035).

Percent below poverty line

This measure is constructed by the ACS as a percentage of the entire county's population reported as living below the poverty line. This measure ranges from zero percentage of the population living below poverty to about half of the population (Maximum=49.500, Average=16.296, $SD_{between}$=6.437). Counties with higher percents of people living below poverty indicate higher levels of social disorganization.

Percent unemployed

This variable captures the percentage of those able to be in the workforce but who are currently unemployed. This measure does not include those under the age of 16 or those who are unable to be in the workforce. The percentage ranges from zero to 27.217 with an average of 8.580 ($SD_{between}$=3.774). Again, high rates of this variable would indicate high levels of social disorganization.

Percent uninsured

This variable captures the percentage of those within a county being reported as without health insurance. Health insurance coverage can be associated with income, employment, and overall wellbeing of a community. High rates of uninsured would indicate high social disorganization. This measure varied greatly, ranging from 2.600 to 66.200 percent of the population without insurance (Average=15.154, $SD_{between}$=5.767).

Percent female headed households

This variable describes the composition of a household. This measure captures the percentage of all households within a county that are headed by a single female with a minor child. Higher proportions of female headed households would indicate higher social disorganization. This measure ranges from 0.000 to 19.297 with an average of 6.479 ($SD_{between}$=2.458).

Percent owner-occupied housing units

Unlike the previous variable, this variable describes housing units, rather than households. Housing units are characterized by the physical entities that house individuals. This variable captures the percentage of housing units within county not only occupied, but occupied by the owner of the unit. Higher proportions of this variable would indicate lower levels of social disorganization. This variable varied greatly and ranges from zero to 94.725 with an average of 72.574 ($SD_{between}$=7.952).

Percent vacant housing units

This variable captures the percentage of housing units that are deemed vacant and are not occupied within the county. Higher levels of vacant housing would indicate social disorganization. This variable also varied extensively, ranging from 1.960 to 78.788 ($SD_{between}$=10.444).

Percent high school educated

The ACS measures education level of individuals at multiple ages. This study limits the measure of education to those 25 years-old or older to ideally capture those who have completed their education while still maintaining the largest sample of individuals possible. This variable measures the percentage of those individuals who have completed their high school education or an equivalent or higher. Higher rates of education would indicate lower levels of social disorganization. This variable ranges from 44.900 to 97.500 with an average of 84.144 ($SD_{between}$=7.041).

Demographic characteristics

This project uses several demographic characteristic variables to limit the amount of noise within the regression models throughout the forthcoming chapters. These measures are able to explain additional variation in the dependent variables and reduce the unexplained variation.

Law enforcement characteristics

The presence of law enforcement within each county is measured by two variables. The CSLLEA counts the number of state and local law enforcement agencies throughout the United States. This time-invariant measure captures the number of agencies operating nationwide in 2008. Each state and local law enforcement agency reports their number of sworn full-time law enforcement officers. A measure of sworn law enforcement officers is the aggregated count by county-years.

Population characteristics

The inclusion of several variables measuring county level population characteristics are included throughout this project. A nine-point continuum code is a measure of *rurality* constructed by the United States Department of Agriculture. This classification measure accounts for population size, density, and proximity to urban areas. A value of one indicates the most urban areas whereas a value of nine indicates the most rural areas. A variable of *total population* is measured by the ACS' estimate of the total number of individuals residing within a county. The ACS reports an estimated measure of *median age* for individuals residing within a county. A *sex-ratio* variable is an estimated count from the ACS of the number of males to each 100 females in a county. This measure estimates the ratio of males to females in each county-year. An *age-dependency* variable is constructed by the ACS as a ratio of those typically of a dependent age to those of a working age. This measure intends to capture the number of dependents to the number of working individuals, based solely on age. Values under 100 indicate a higher proportion of working age individuals whereas values over 100 indicate higher proportions of dependent age. Lastly, a *percentage of White individuals* is constructed by the ACS as a percentage of the entire county's population who reported their race as only White.

Data Considerations

Although these data allow for fruitful findings discussed in forthcoming chapters, they are not without limitations. The difficulties constructing this dataset presented me with several subjective decisions, which led to deeper considerations.

NIBRS vs. UCR

A measure of general crime needs to be included within the dataset to adequately explore the research questions. This needs to be a longitudinal measure that captures crime on a county level. Ultimately, the decision came down to the NIBRS or the UCR.

The NIBRS was created to collect and maintain detailed information about criminal *incidents* across the United States and territories (see *National Incident-Based Reporting System*, 2023). Local, regional, and state agencies collect information about the incidents, offenders, and victims of criminal incidents within their jurisdiction. These data are voluntarily shared with the FBI who maintain the aggregate of data. During the years of this study, this system was entirely voluntary, and many agencies opted out of submitting these data. Due to this, many county-years lacked any reporting from agencies or only a small proportion of agencies participated in this voluntary submission. This led to a greatly reduced sample size of county-years which could be used to explore the research questions.

The UCR was the standard reporting system for many years prior to the onset of NIBRS. More recently the FBI has made the implementation of NIBRS a nationwide top priority to improve the overall quality of crime data collected by law enforcement (*National Incident-Based Reporting System*, 2023). Due to this shift in priorities, UCR data are not available after 2016. This limits the study years by one year. The shift to NIBRS is well justified. The UCR provides far less data compared to the comprehensive nature of NIBRS data. The incident-based data provided by NIBRS has the ability to include several offense variables for each incident, as well as information about the victims and offenders. A major limitation of UCR data is the inability to do this.

The research questions presented in this dissertation do not require the inclusion of incident-based information, but rather a general measure of crime. Based on the coverage limitations of NIBRS, the UCR is used for this current project. Future research should continue the inclusion of NIBRS data within studies as it includes tremendous amounts of incident-based information and the representativeness across the United States appears to only be improving.

Police crime committed in the officer's official capacity

An additional variable was considered. This variable measured the proportion of police crime that was committed within a law enforcement officer's official capacity. Crime committed within an officer's official capacity refers to criminal behavior committed while on-duty or while the law enforcement officer "invoked any aspects of the officer's status as a sworn law enforcement officer" (Stinson, 2023).

This measure offers a key context in relation to the outcome measure. Instead of capturing all crimes committed by law enforcement officers like the dependent variable, this measure captures the proportion of police crime within a county-year where the officers used their powers as law enforcement to commit the criminal behavior. This could include on-duty offenses or off-duty offenses in which the officers abused their authority to commit the crime. An example of this would be an officer seeking leniency by flashing their badge or identifying themselves as law enforcement.

The police crime in official capacity proportion measure is constructed by dividing the number of police crime cases committed in the officers' official capacity by all police crime cases for each county-year. This measure ultimately captures the proportion of police crime in which the arrested officers used their authority as law enforcement to commit the criminal behavior. The Henry A. Wallace Police Crime Data captured 2,758 cases of police crime committed in the officer's official capacity during the study years, 2013-2017. A count of official capacity cases would be divided by the total cases of police crime to calculate a measure of the proportion of police crimes that were committed in an officer's official capacity within a specific county-year. However, in many instances, the count of police crimes within a county-year is equal to zero, meaning there were no cases of police crime identified. In these instances, a calculation for the proportion of official capacity crimes would result in an undefined value. There were too many zero counts of police crime throughout the county-years of the study to provide reasonable justification for inclusion of this proportion measure. Therefore, this control measure was not used throughout analysis. Additional research should continue to explore the phenomenon of law enforcement officers committing crimes using their official capacity.

CHAPTER V. COUNTY LEVEL CORRELATES OF POLICE CRIME

Researchers have drawn on traditional criminological theories to explain police misconduct for decades. Scholars have found support for strain, control, and learning theories (Donner et al., 2021). Strain theorists explain how the unique stressors of the job may influence police officers to engage in misconduct (Bishopp et al., 2016, 2019, 2020). Control theorists posit that self-control may impact an officer's participation in deviant behaviors and social-control may explain why officers may adhere to a "code of silence" (Donner et al., 2018; Donner et al., 2016b; Donner & Jennings, 2014). Lastly, learning theories explore how learning can occur among colleagues within a police department (Chappell & Piquero, 2004). Despite these meaningful applications of criminological theories, we still may not have a complete understanding of police crime. Researchers have found that individual level criminological theories may not solely explain police crime and that the field should expand to include a more macro level lens (Wood et al., 2019). Coupled with the current literature, a structural perspective could provide a more thorough understanding of police crime throughout the United States.

This analytical chapter aims to investigate police crime from a structural perspective. At the time of this study, there exists no known nationwide quantitative study exploring a structural criminological theory, to my knowledge. The current study is built upon the foundation of understanding from Kane's work on the social ecology of police misconduct (see Kane, 2002). This work explores the social structures of police misconduct and alludes that social disorganization may provide a valuable insight to the study of police crime.

Analytical Approach

The goal of this nationwide analysis of panel data is to explore police crime and county level characteristics, with an emphasis on measures of social disorganization. This chapter aims to answer the following research question: what are the significant county level correlates of police crime (RQ1)? Based on social disorganization theory, I hypothesize that the proxy measures of social disorganization will be significantly associated with police crime (H1). If this hypothesis is to be supported, counties with more social disorganization will have more crime committed by law enforcement officers.

The sample for this analysis includes all 3,143 American counties (or county-equivalents, such as independent cities, parishes, or boroughs) across five years (2013-2017), totaling 15,715 county-years. This analytical chapter does not use data from the UCR, so the sample does not need to be limited by the percentage of agencies reporting. The CSLLEA does not capture 10 counties, primarily in Alaska, due to the changes in county boundaries since 2008. These county-years will be excluded in the multivariate analysis. The multivariate analysis will include 3,133 counties. Each county will include exactly five years of data, ranging from 2013 to 2017. This nearly complete sample of the American counties is a rarity within social science research and serves as a unique strength of this study.

Table 3 explores the descriptive statistics of the variables included in this analysis. The dependent variable for this chapter is a count of police crime. This measure is time-varying across five years of data for all 3,143 American counties. The average count of police crime within a county-year is 0.400 cases. Based on Figure 2 and the dispersion statistics, this measure appears to be positively skewed with many zero values. Many transformations for this variable are considered. Ultimately, an integer is added to the values and then the variable is transformed using a natural log transformation for this analysis. This transformation reduces the skewness of the dependent variable.

Table 3. Descriptive Characteristics of Variables Used in Analyses for Chapter V; n=3,143 Counties.

	Time-variant or time-invariant	*n* (county-years)	*n* (counties)	Mean	SD (between)	SD (within)	Range
Dependent variable							
Police crime	T.V.	15,715	3,143	0.400	1.331	0.791	0.000 – 42.000
Social disorganization variables							
Gini index	T.I.	3,143	3,143	0.435	0.035	---	0.316 – 0.599
Percent female headed households	T.I.	3,142	3,142	6.479	2.458	---	0.000 – 19.297
Percent owner-occupied housing units	T.I.	3,143	3,143	72.574	7.952	---	0.000 – 94.725
Percent vacant housing units	T.I.	3,143	3,143	17.656	10.444	---	1.960 – 78.788
Cumulative disadvantage scale							
Scale items							
Percent below poverty line	T.I.	3,143	3,143	16.296	6.437	---	0.000 – 49.500
Percent unemployed	T.I.	3,143	3,143	8.580	3.774	---	0.000 – 27.217
Percent uninsured	T.I.	3,143	3,143	15.154	5.767	---	2.600 – 66.200
Percent high school educated	T.I.	3,143	3,143	84.144	7.041	---	44.900 – 97.500
Overall scale							
Cumulative disadvantage	T.I.	3,143	3,143	13.972	4.706	---	4.139 – 36.952
Demographic characteristics							
Law enforcement agencies	T.I.	3,133	3,133	5.738	7.219	---	1.000 – 135.000
Sworn law enforcement officers	T.I.	3,133	3,133	244.241	1,137.909	---	0.000 – 37,503.000
Rurality	T.I.	3,143	3,143	5.008	2.709	---	1.000 – 9.000
Total population / 10,000	T.I.	3,143	3,143	9.836	31.370	---	0.007 – 984.002
Sex ratio	T.I.	3,143	3,143	100.568	12.169	---	73.400 – 325.000
Age-dependency ratio	T.I.	3,143	3,143	65.453	10.244	---	6.300 – 115.000
Percent White	T.I.	3,143	3,143	83.908	16.663	---	3.110 – 100.000

The social disorganization variables are the focal independent variables for this chapter. These variables provide a range of characteristics associated with social disorganization. These variables include measures of income inequality and distribution, employment and insurance statuses, compositions of households and housing units, and the educational attainment of the county. With the exception of the percent of owner-occupied housing units and educational attainment measures, higher values for these measures indicate higher levels of social disorganization. Table 3 explores the averages, ranges, and dispersions of each of these variables. These variables are first examined as individual items but the correlations between some of these variables cause concern for multicollinearity throughout the model building process. After running tests for multicollinearity, it is determined that the percent poverty, percent high school educated (reverse coded), percent unemployed, and percent insurance variables would perform well as a scale. These variables load together with a value for Cronbach's alpha of 0.812. This scale will represent the cumulative disadvantage of the county. Additional variables such as Gini index and percent of female headed households were considered for the scale but ultimately lowered the scale's reliability. Tolerance statistics, variance inflation factors (VIFs), and correlations are examined throughout the analysis to explore any further issues of multicollinearity. The number of sworn law enforcement officers is correlated with the number of law enforcement agencies within a county. The variable measuring the number of officers is excluded from the multivariate analysis. Lastly, the percent of female headed households is excluded from the analysis due to concerns of multicollinearity. With the remaining variables, the standard thresholds are satisfied for tolerance statistics and VIFs (see Allison, 1999). The highest VIF is 1.90 and the lowest tolerance value is 0.527. This presents minimal concerns for multicollinearity throughout the multivariate analysis.

This chapter uses a series of two-level, mixed-effects models. This type of model has been traditionally used for longitudinal, panel datasets (Rabe-Hesketh & Skrondal, 2012), similar to the one constructed for this study. A multilevel model is needed for these data due to the dependency among observations (Rabe-Hesketh & Skrondal, 2012). Each observation, or each county-year, is not independent from other county-years. Counties are measured five times throughout the data. Years (level one) will be nested in counties (level two).

Mixed-effects models are versatile because they model both random- and fixed-effects. To fully understand the complexity of a mixed-effects model, it is important to first understand the individual, fixed and random parts of the model. Both fixed- and random-effects models could be used to model nested data. A fixed-effects model would measure within-level-two change. In the case of this study, a fixed-effects model would measure within-county change. These models are used for longitudinal data because of the ability to measure change in observations over time. Whereas, a random-effects model would be used to model between-county change. For this study, a mixed-effects model grants me the ability to capture both within-county and between-county variation. This statistical approach is conceptually the most appropriate model for these data. The two-level, mixed-effects models used throughout this dissertation can be stated by the following formula (Laird & Ware, 1982):

$$y_{ij} = \beta_0 + \sum \beta_p x_{ij} + \sum b_q z_i + \varepsilon_{ij}$$

This generic formula describes the basic elements of a mixed-effects model for longitudinal data. This formula regresses variable y (time j is nested in county i) onto time-variant and time-invariant predictors. The β_0 term denotes the global constant term. The summation of $\beta_p x_{ij}$ terms indicate the fixed-effects portion of this model which models the time-variant variables. The β_p terms represent the fixed-effects coefficients and the x_{ij} terms represent the regressors for time *j* nested in county i. The summation of $b_q z_{ij}$ terms indicate the random-effects portion of this model which model the time-invariant variables. The b_q terms represent the random-effects coefficients and the z_{ij} terms represent the regressors for variable *i*. Lastly, ε_{ij} represents the error term.

This analytical chapter explores a series of mixed-effects models regressing police crime on predictors. Traditionally, a Hausman test is used to determine if a fixed-effects model is more suitable than a random-effects model. The independent variables used throughout these models in this analytical chapter are time invariant. This makes it unfeasible to use a fixed-effects model to capture within county change. The models used with these data are only able to capture the between county effects of the dependent variable despite the within county change across the years of the study. The first model within this chapter solely examines the effects of the social disorganization variables on police crime. The following models include all previous variables with the inclusion of the demographic characteristic variables. The second model introduces a measure of law enforcement presence. The third and final model introduces population characteristics.

When applying the model formula to the current context, the formula specific to this chapter can be written as follows:

$$(police\ crime)_{ij} = \ \beta_0 + \sum b_q(TISDV)_i + \sum b_q(TICV)_i + \varepsilon_{ij}$$

This specific formula model regresses police crime on time-invariant predictors. Year *j* is nested in county i. The β_0 term denotes the global constant term of police crime across time and counties. The two b_q terms indicate the random-effects portion of this model. Each b_q value indicates the random-effects coefficients. This models the time-invariant variables. The $(TISDV)_i$ terms represent the time-invariant, social disorganization variables for county i. The

$(TICV)_i$ terms represent the time-invariant, control variables for county i. The ε_{ij} term represents the error term.

Multivariate Results

Table 4 displays the mixed-effects models regressing police crime onto social disorganization variables and demographic characteristic measures. As explained earlier, concerns of multicollinearity are thoroughly examined, and the standard thresholds are satisfied for tolerance statistics and VIFs. The intraclass correlation value (rho=0.576) indicates moderate correlation within counties. Coupled with the inherent two-level nature of the data, this confirms the need for multilevel models. The models presented in Table 4 are using standardized coefficients and bootstrapped standard errors. Each model presented was able to significantly explain variation in police crime throughout the United States. Model 1 in Table 4 presents results from the mixed-effects model regressing police crime on the social disorganization variables. All social disorganization variables are significant, meaning police crime is significantly associated with these antecedents of social disorganization. The significance of the social disorganization variables suggests the variation of police crime throughout the United States can partly be explained by the tenets of social disorganization theory. As hypothesized (H1), higher levels of inequality and less owner-occupied housing units are associated with higher counts of police crime within counties. Opposing my first hypothesis (H1), less vacant housing and less cumulative disadvantage is correlated with higher counts of police crime. Demographic variables are considered in the following models to gain a more complete understanding of the structural level predictors of police crime.

Table 4. Mixed-Effects Models Regressing Police Crime on Predictors; n=3,133 Counties.

	Model 1		Model 2		Model 3	
	b_z	BSE	b_z	BSE	b_z	BSE
Social disorganization variables						
Gini index	.074	.003***	.032	.002***	.026	.002***
Percent owner-occupied housing units	-.118	.003***	-.089	.003***	-.046	.003***
Percent vacant housing units	-.044	.002***	-.006	.002**	.021	.002***
Cumulative disadvantage	-.062	.003***	-.020	.002***	-.026	.003***
Demographic characteristics						
Law enforcement agencies	--	--	.203	.004***	.088	.006***
Rurality	--	--	--	--	-.062	.003***
Total population / 10,000	--	--	--	--	.154	.010***
Sex ratio	--	--	--	--	-.015	.002***
Age-dependency ratio	--	--	--	--	.000	.002
Percent White	--	--	--	--	-.038	.003***
Intercept	.172	.002***	.173	.002***	.172	.002***
Model statistics						
Wald χ^2	2,873.08***		4,321.60***		5,223.86***	
Between cluster variance	0.084		0.084		0.084	
Within cluster variance	0.088		0.052		0.032	

* $p \le .05$; ** $p \le .01$; *** $p \le .001$

Model 2 in Table 4 presents results from the mixed-effects model regressing police crime on the social disorganization variables and law enforcement control. With the inclusion of the significant law enforcement variable, all social disorganization variables remain significant. This means that the social disorganization variables remain significantly associated with police crime despite the also significant relationship between police crime and police presence throughout the United States. Similar to Model 1, higher levels of inequality and less owner-occupied housing units are associated with higher counts of police crime within counties but more vacant housing and more cumulative disadvantage is correlated with lower counts of police crime. The varied directions of these results suggest that social disorganization theory may produce mixed results as it is applied to police crime throughout the United States. These mixed results will be discussed further in the discussion chapter (see Chapter VIII).

Model 3 in Table 4 concludes the findings from the mixed-effects model regressing police crime on the social disorganization variables and all remaining variables. With the inclusion of demographic characteristic measures, complex relationships are revealed. All social disorganization variables remain significant. Consistent with the prior two models, higher levels of inequality and less owner-occupied housing units correlate with higher counts of police crime. These findings are consistent with the theoretical framework. The percent of vacant housing units remains significant, but in this final model is positively associated with police crime. This variable has switched from negatively associated with police crime in Models 1 and 2, to positively associated with police crime in Model 3. This relationship will be explored in the final discussion chapter. The positive association can be interpreted to mean that counties with more vacant housing are likely to experience more police crime. This is in support of the first hypothesis which proposes that counties with higher levels of social disorganization are likely to be associated with higher counts of police crime. The cumulative disadvantage variable remains significantly associated with police crime. This correlation can be interpreted to mean that counties with less cumulative disadvantage would likely have higher counts of police crime. Similarly, counties with more cumulative disadvantage are likely to have lower counts of police crime. The direction of this finding remains puzzling and cannot be adequately, empirically explained by my theatrical framework. This might suggest that the application of social disorganization theory to police crime may be more complex than these data are able to capture. A more comprehensive discussion of this result is included in the concluding chapter. Among the demographic variables, the only insignificant variable is the age-dependency ratio. The number of law enforcement agencies and total population variables are positively associated with police crime, whereas, the rurality, sex ratio, and percent White variables are negatively associated with police crime.

These mixed results suggest the need for continued exploration of police crime at a structural level. The following chapter introduces an examination of general crime. The findings of these two analytical chapters will guide the third and final analytical chapter. This chapter will further explore police crime at a structural level by examining the relationship between general crime and police crime. The remaining analytical chapters aim to provide a more complete understanding of police crime through a structural perspective.

Sensitivity Analysis

The models presented in Table 4 were re-estimated without bootstrapped standard errors. These re-estimated models can be found in a table in Appendix C. The models presented with regular and replicated standard errors are very similar. One notable difference between the models is the significance of the percent vacant housing variable in Model 2 of Table 4, but insignificance in Appendix C. The direction and significance of the relationship between vacant housing and police crime will be discussed further in the final discussion chapter of this dissertation. All other significance and directions of coefficients remain consistent between the bootstrapped and regular models. This further confirms the findings reported in this chapter.

CHAPTER VI. COUNTY LEVEL CORRELATES OF GENERAL CRIME

The previous chapter regressed police crime on county level predictors. I hypothesized that the measures of social disorganization would prove to be significant predictors of police crime at a structural level. While these meaningful results revealed significant correlates of police crime, it is important to explore how these same predictors may also be associated with general crime. Social disorganization theorists posit that communities are confronted with a "complex social phenomenon" (Sampson, 2012, p. 55). The structural characteristics that are associated with police crime may not be the same structural characteristics associated with general crime. The similarities and differences in county level correlates of police crime and general crime may reveal some otherwise unknown characteristics of this complex social phenomenon.

Analytical Approach

The goal of this analytical chapter is to explore the similarities and differences in the significant structural predictors of general crime and police crime. The primary research question for this chapter asks whether the significant correlates of general crime are the same for police crime at a structural level (RQ2). Based on social disorganization theory, I hypothesize measurements of social disorganization are significantly associated with general crime (H2). If this hypothesis is supported, the significant predictors of general crime would be similar to the significant predictors of police crime (as hypothesized in Chapter V).

The sample for this analysis is limited by the data available from the UCR. First, county-years with no available UCR data are excluded from the analysis. Second, I explored cutoff options for the percentage of agencies reporting variable constructed from the UCR and CSLLEA data. This variable is largely constructed to exclude the most extreme cases of underreporting; therefore a 50% cutoff is used for this chapter. Lastly, the UCR data spans from 2013 to 2016 which limits the study years of this chapter. The final analytical sample for this chapter includes 2,511 counties (or county-equivalents, such as independent cities, parishes, or boroughs), with an average of 3.67 years of data for each county over the four-year study period, 2013-2016.

Table 5 displays the descriptive statistics of the variables included within this analysis. The dependent variable for this chapter, general crime, ranges from 0 to 120,503 reported general crimes within a county-year. The average for this measure is 2,354.085, as displayed in Table 5. Similar to Chapter V, transformations were explored for the dependent variable due to the skewness of the variable. Ultimately, the same natural log transformation was used for this chapter. The social disorganization variables remain the focal independent variables for this chapter. As explored in Chapter V, these variables include measures of income inequality and distribution, employment and insurance statuses, compositions of households and housing units, and the educational attainment of the counties. Table 5 explores the averages, ranges, and dispersions of each of these variables with the limited analytical sample for this chapter. Because the independent variables remain the same, the data exploration discussed in Chapter V is relevant for this chapter. Again, a cumulative disadvantage scale is used to capture percent poverty, percent high school educated (reverse coded), percent unemployed, and percent insured. As discussed in Chapter V, the number of law enforcement officers and the percent of female headed households are not included throughout the multivariate analysis due to concerns of multicollinearity. I further examined tolerance statistics, VIFs, and correlations using this chapter's limited sample and found no additional concerns of multicollinearity.

Table 5. Descriptive Characteristics of Variables Used in Analyses for Chapter VI; n=2,511 Counties.

	Time-variant or time-invariant	*n* (county-years)	*n* (counties)	Mean	SD (between)	SD (within)	Range
Dependent variable							
General crime (UCR)	T.V.	9,478	2,511	2,354.085	4,647.698	313.800	0.000 – 120,503.000
Social disorganization variables							
Gini index	T.I.	2,511	2,511	0.434	0.034	---	0.332 – 0.564
Percent female headed households	T.I.	2,511	2,511	6.339	2.363	---	0.000 – 18.947
Percent owner-occupied housing units	T.I.	2,511	2,511	72.400	7.673	---	29.816 – 94.725
Percent vacant housing units	T.I.	2,511	2,511	17.353	10.459	---	1.968 – 78.788
Cumulative disadvantage scale							
Scale items							
Percent below poverty line	T.I.	2,511	2,511	15.962	6.250	---	0.000 – 49.500
Percent unemployed	T.I.	2,511	2,511	8.479	3.706	---	0.000 – 26.194
Percent uninsured	T.I.	2,511	2,511	14.707	5.370	---	2.600 – 45.200
Percent high school educated	T.I.	2,511	2,511	84.587	6.852	---	53.700 – 97.500
Overall scale							
Cumulative disadvantage	T.I.	2,511	2,511	13.640	4.517	---	4.139 – 3.993
Demographic characteristics							
Law enforcement agencies	T.I.	2,511	2,511	5.703	7.233	---	1.000 – 112.000
Sworn law enforcement officers	T.I.	2,511	2,511	238.338	850.280	---	0.000 – 25,485.000
Rurality	T.I.	2,511	2,511	4.929	2.717	---	1.000 – 9.000
Total population / 10,000	T.I.	2,511	2,511	10.197	31.052	---	0.009 – 984.002
Sex ratio	T.I.	2,511	2,511	100.105	10.669	---	73.400 – 325.000
Age-dependency ratio	T.I.	2,511	2,511	65.084	9.998	---	6.300 – 111.200
Percent White	T.I.	2,511	2,511	85.036	15.897	---	3.552 – 100.00

Similar to the previous chapter, this chapter uses a model-building process with a series of mixed-effects regression models. Again, years are nested within counties. The model building process is identical to Chapter V with respect to the inclusion of independent variables. The first model within this chapter solely examines the effects of the social disorganization variables on general crime. The second model introduces a law enforcement presences variable, and the third model introduces the variables capturing demographic characteristics. The models from this chapter and Chapter V have the same independent variables so I am able to adequately compare models.

The mixed-effects models specific to this analytical chapter can be written with the following formula:

$$(general\ crime)_{ij} = \beta_0 + \sum b_q(TISDV)_i + \sum b_q(TICV)_i + \varepsilon_{ij}$$

This formula denotes the mixed-effects model which regresses general crime on time-invariant predictors. Year *j* is nested in county *i*. The global constant term of general crime across time and counties is represented by the β_0 term. The next two components of the model indicate the time-invariant variables, modeled by random-effects. These are the two b_q terms. Each b_q value indicates the random-effects coefficients. The $(TISDV)_i$ terms represent the one time-invariant, social disorganization variable for county *i*. The $(TICV)_i$ terms represent the time-invariant, control variables for county *i*. The ε_{ij} term represent the error term.

The independent variables used in the models for this chapter and the prior chapter are the same. This allows for an accurate comparison of the models by employing a Clogg test. This method examines the statistical equality of coefficients from multiple regression models (Clogg et al., 1995). In other words, the Clogg test will determine whether the coefficients of Chapter V's models are significantly different than those of this chapter's models. This comparison of coefficients elaborates beyond just determining if the same variables are significant, but further reveals if the magnitude of these coefficients differs between models. For the most accurate comparison, I will re-model Chapter V's models using the same limited sample as this chapter.

Multivariate Results

Table 6 presents the mixed-effects models regressing general crime onto social disorganization variables and demographic variables. The intraclass correlation value (rho=0.966) reveals a strong correlation within counties for these models. The models presented in Table 6 are using standardized coefficients and bootstrapped standard errors, just like the previous chapter.

The first model in Table 6 regresses general crime on the social disorganization variables. All social disorganization variables are significant in Model 1. Gini index is positively associated with general crime and percent of owner-occupied housing units is negatively associated with general crime. This suggests that counties with greater income inequality or less owner-occupied housing units tend to have more general crime reported. The percent vacant housing units is negatively correlated with general crime. This would suggest that counties with fewer vacant housing units tend to have more general crime. Lastly, the cumulative disadvantage variable is also negatively associated with general crime. Counties with less cumulative disadvantage are likely to experience more general crime. The following two models continue to explore the relationship between precursors of social disorganization and general crime.

Model 2 in Table 6 regresses general crime on social disorganization variables with the inclusion of a variable that captures the number of law enforcement agencies within the county. This model was also able to significantly explain variation in the general crime measure. The

Table 6. Mixed-Effects Models Regressing General Crime on Predictors; *n*=2,511 Counties.

	Model 1		Model 2		Model 3	
	b_z	BSE	b_z	BSE	b_z	BSE
Social disorganization variables						
Gini index	.188	.009***	.031	.008***	-.006	.007
Percent owner-occupied housing units	-.440	.009***	-.334	.008***	-.161	.009***
Percent vacant housing units	-.553	.008***	-.415	.007***	-.092	.007***
Cumulative disadvantage	-.139	.009***	.031	.008***	.121	.008***
Demographic characteristics						
Law enforcement agencies	--	--	.733	.009***	.440	.009***
Rurality	--	--	--	--	-.626	.009***
Total population / 10,000	--	--	--	--	.067	.013***
Sex ratio	--	--	--	--	-.245	.007***
Age-dependency ratio	--	--	--	--	-.355	.009***
Percent White	--	--	--	--	-.006	.009
Intercept	6.670	.007***	6.668	.006***	6.671	.005***
Model statistics						
Wald χ^2	18,503.39***		26,925.25***		61,979.08***	
Between cluster variance	0.088		0.088		0.088	
Within cluster variance	1.862		1.391		0.884	

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

significance of the Gini index, percent owner-occupied housing units, and vacant housing unit variables can be interpreted the same as Model 1 in Table 6. The cumulative disadvantage variable remains significant but the direction of the coefficient switches to positive. This implies that counties with more cumulative disadvantage tend to experience more reported general crime. This positive relationship between cumulative disadvantage and general crime is consistent with my theoretical framework as it suggests that structurally disadvantaged counties are often experiencing more general crime. The number of law enforcement agencies is also positively associated with general crime. Counties with more law enforcement agencies are often experiencing more general crime.

The final model in Table 6 regresses general crime on social disorganization and demographic variables. The Gini index variable is no longer significant, but all other social disorganization variables remain significant. This indicates that the demographic variables included within the final model now explain the variation previously explained by the Gini index variable. All other social disorganization variables also significantly explain variation in the general crime measure. The percent of owner-occupied housing units variable is negatively associated with general crime, meaning counties with fewer owner-occupied housing units are likely to have more general crime. The percent vacant housing units variable is negatively correlated with general crime. This would suggest that counties with less vacant housing units tend to experience more general crime. The cumulative disadvantage variable remains positively associated with general crime. Again, this suggests that counties with more cumulative disadvantage are likely to also have more general crime. Many of the demographic variables in Model 3 in Table 6 are significantly associated with general crime. The number of law enforcement agencies and total population variables are positively associated with general crime.

The rurality, sex ratio, and age dependency ratio variables are negatively correlated with general crime. The percent White variable is insignificant within this model. Further exploration of these mixed findings will be discussed in the final discussion chapter (see Chapter VIII).

The models reported in Chapter V can be compared to the models reported in this chapter to determine the similarities in significant correlates between police crime and general crime at a structural level. This comparison is completed using a Clogg test with unstandardized coefficients. For the most accurate comparison, I re-estimated my models from Chapter V with the same limited analytical sample used throughout this chapter. Table 7 reports the models and results from the Clogg test.

The Clogg test reported in Table 7 reveals stark differences between models regressing police crime and general crime. The coefficients associated with the independent variables are all significantly different between models regressing police crime and general crime, indicating that the relationship between the independent variables and police crime are significantly different than the relationships between these same variables and general crime. The majority of the differences are related to variables that are significant in both models but the magnitudes of the coefficients are significantly different. This is true for the percent owner-occupied housing units variable and many demographic variables. Another type of significant difference revealed by the Clogg test are coefficients that are significant in one model, but insignificant in the other. This significant difference can be reported for the Gini index, age dependency ratio, and percent White variables. The last type of difference discovered by the Clogg test are coefficients that change direction but remain significant between model regressing police crime and general crime. The percent vacant housing variable is significant in both models but positively associated with police crime and negatively associated with general crime. Likewise, the cumulative

Table 7. Clogg Test for Models Regressing Police Crime and General Crime on Unstandardized Predictors; *n*=2,511 Counties.

	Police Crime		General Crime		Clogg Test
	b	BSE	b	BSE	Z
Social disorganization variables					
Gini index	.607	.093***	.160	.205	1.986*
Percent owner-occupied housing units	-.005	.001***	-.020	.001***	13.416***
Percent vacant housing units	.002	.000***	-.009	.001***	10.536***
Cumulative disadvantage	-.004	.001***	.026	.002***	-13.416***
Demographic characteristics					
Law enforcement agencies	.016	.001***	.061	.001***	-31.678***
Rurality	-.018	.002***	-.231	.004***	51.660***
Total population / 10,000	.004	.000***	.002	.002**	3.536***
Sex ratio	-.002	.000**	-.020	.001***	17.650***
Age-dependency ratio	-.001	.000	-.035	.001***	32.566***
Percent White	-.003	.000***	-.000	.001	-2.490*
Intercept	.700	.069***	12.975	.513***	-73.135***
Model statistics					
Wald χ^2	3,062.32***		52,342.51***		
Between cluster variance	0.088		0.088		
Within cluster variance	0.029		.884		

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

disadvantage variables is significant in both models but negatively associated with police crime and positively associated with general crime. These findings reveal that the structural level correlates of police crime and general crime are significantly different. Empirically, this demonstrates that the social disorganization variables are performing differently for explaining general crime and police crime. This would suggest that social disorganization theory may be a valid theoretical framework for explaining both general crime and police crime, but the applications of the theory may vary across and within the populations under examination. Further implications of these findings will be discussed in the final chapter of this dissertation.

Sensitivity Analysis

The bootstrapped models presented throughout this chapter were re-estimated using regular standard errors. The same model building process was used with regular standard errors and these re-estimated models are reported in Appendix D. The re-estimated models remain significant. The models with regular and bootstrapped standard errors are very similar. The most prominent difference is the cumulative disadvantage variable in Model 2 in Appendix D is insignificant, unlike the variable in Model 2 in Table 6. Similar to the results from the sensitivity analysis from Chapter V, this variable changes direction throughout the bootstrapped models and is insignificant in the regular, re-estimated models. These unexpected findings will be discussed in the final discussion chapter of this dissertation. All other variables have the same significance and directions of coefficients between the bootstrapped and regular models. These findings confirm the robustness of the results reported throughout this chapter.

The Clogg test reported in this chapter uses the same limited analytical sample for both general crime and police crime. The models reported in Chapter V use a larger sample. The models from Chapter V were re-estimated using unstandardized coefficients so a comparison can be made using a Clogg test. Appendix E reports the re-estimated model regressing police crime onto unstandardized coefficients with a larger sample, the original model regressing general crime onto unstandardized coefficients, and a comparison of these models using a Clogg test. The table reported in Appendix E can be compared to Table 7 which reports the original Clogg test. The Clogg tests reported in Appendix E and Table 7 are very similar. The difference in coefficients for the percent White variable is now insignificant. The comparisons of all other variables remain significant, like reported in Table 7. The direction of the percent vacant housing and cumulative disadvantage variables are again different between models regressing police crime and general crime, just like Table 7. The similarities between the Clogg tests reporting in Appendix E and Table 7 confirm the findings reported throughout this chapter.

CHAPTER VII. WHAT IS THE RELATIONSHIP BETWEEN GENERAL CRIME AND POLICE CRIME?

The prior two analytical chapters explored how social disorganization variables relate to police crime and general crime. It was found that the social disorganization variables partly explained the variation of police crime and general crime. These results indicate the relationship between police crime, general crime, and structural level characteristics is not simple. The relationship between police crime and general crime is not something that can be fully understood by the comparison of statistical models, as completed in the prior chapters. Rather, it should be examined whether general crime itself is associated with police crime from a structural perspective. Furthermore, it may be possible for police crime to serve as a significant predictor of general crime. This potential interwoven relationship between these variables has not yet been explored from a structural perspective. This analytical chapter aims to better understand the relationship between general crime, police crime, and social disorganization variables.

It is important to develop an understanding of police crime from a structural perspective in order to grasp the full scope of the phenomenon. This should include an understanding of how police crime is related to general crime. Without this full structural understanding, criminologists and policy makers may inadvertently create policies that influence general crime and police crime in contradictory ways. By advancing the understanding of police crime from a structural perspective, this dissertation is able to inform meaningful policy implications for police agencies, advocates, and community leaders.

Analytical Approach

As revealed in the prior two analytical chapters, there exists a complex structural understanding of general crime and police crime worthy of continual examination. This final analytical chapter aims to explore this potential interconnected relationship. The previous analytical chapter explored the similarities and differences between the significant structural predictors of general crime and police crime. The variables aimed at measuring a proxy of social disorganization were found to be a partial explanation for the variation in police crime (see Chapter V) and general crime (see Chapter VI). This chapter explores general crime and police crime from a different approach. From a social disorganization theory perspective, the relationship between general crime and police crime could manifest in different ways. This chapter examines police crime and general crime simultaneously and determines if general crime influences police crime, or vice versa.

With a lagged general crime variable, this chapter explores whether general crime is a significant predictor of police crime. The primary research question of this chapter is as follows: is there a significant relationship between general crime and police crime at a structural level (RQ3)? I hypothesize there is a significant and positive relationship between general crime and police crime (H3). If this hypothesis is supported, county-years with higher measures of general crime will also experience higher counts of police crime throughout the United States. In pursuit of a complete understanding of these structural variables, I will also explore whether police crime is a significant predictor of general crime, using a lagged police crime variable.

The statistical approach to this final analytical chapter is very similar to the previous two chapters, now with the inclusion of a lagged independent variable. Lagged independent variables are commonly used within social science research (Bellemare et al., 2017). The purpose of a lagged independent variable is to measure the effects of the variable, while taking into consideration the time it may take to witness those effects. For this study, I regress police crime on a lagged measure of general crime. The general crime variable is lagged by one year. The

2012-2016 general crime data is modeling 2013-2017 police crime. Conceptually, general crime within a county may not immediately influence the behavior of police. Over time (modeled with a lagged independent variable), I would hypothesize that general crime will be significantly associated with police behaviors, specifically police crime.

The sample used for the multivariate analyses for this analytical chapter is limited by the UCR data. The focal independent variables for this chapter are measured by the UCR data, therefore it is essential my analytical sample includes complete data for the measures of general crime. First, county-years with no available UCR data are excluded from the analysis. Second, I include the percentage of agencies reporting variable constructed from the UCR and CSLLEA data, just as I did in Chapter VI. It is crucial this variable is closely examined to exclude the most extreme cases of underreporting. Similar to Chapter VI, I explore possible cutoff values for this analytical sample and ultimately a cutoff value of 50% is selected. County-years with fewer than half of the agencies reporting to UCR are not included within the multivariate analysis. Because of the lagged nature of my focal independent variable, I now include UCR data from 2012. I am now able to model police crime for the years 2013-2017. The descriptive results for this chapter include 2,542 counties (or county-equivalents, such as independent cities, parishes, or boroughs), with an average of 4.6 years of data for each county over the five-year study period, 2013-2017.

Descriptive statistics of the variables used in this chapter are displayed in Table 8. The dependent variable for this chapter is a count of police crime. This measure ranges from zero to 42.000 cases of police crime, with an average of 0.398 cases per county-year. Figure 2 and the dispersion statistics reveal that this variable is positively skewed with a large amount of zero values. Similar to the previous two analytical chapters, transformations were explored. The dependent variable was ultimately transformed using a natural log transformation.

Table 8. Descriptive Characteristics of Variables Used in Analyses for Chapter VII; n=2,542 Counties.

	Time-variant or time-invariant	*n* (county-years)	*n* (counties)	Mean	SD (between)	SD (within)	Range
Dependent variable							
Police crime	T.V.	11,788	2,542	0.398	1.269	0.797	0.000 – 42.000
Focal independent variables							
Lagged general crime (UCR)	T.V.	11,788	2,542	2,390.854	4,686.317	355.649	0.000 – 125,073.000
Lagged crimes against persons (UCR)	T.V.	11,788	2,542	472.047	981.404	70.431	0.000 – 26,436.000
Lagged crimes against property (UCR)	T.V.	11,788	2,542	571.6157	1,260.341	107.919	0.000 – 37,252.000
Lagged crimes against society (UCR)	T.V.	11,788	2,542	1,347.192	2,486.614	212.451	0.000 – 61,385.000
Social disorganization variables							
Gini index	T.I.	2,542	2,542	0.434	0.034	---	0.332 – 0.564
Percent female headed households	T.I.	2,542	2,542	6.334	2.373	---	0.000 – 18.947
Percent owner-occupied housing units	T.I.	2,542	2,542	72.384	7.714	---	29.816 – 94.725
Percent vacant housing units	T.I.	2,542	2,542	17.353	10.440	---	1.968 – 78.788
Cumulative disadvantage scale							
Scale items							
Percent below poverty line	T.I.	2,542	2,542	15.947	6.294	---	0.000 – 49.500
Percent unemployed	T.I.	2,542	2,542	8.460	3.722	---	0.000 – 26.194
Percent uninsured	T.I.	2,542	2,542	14.708	5.380	---	2.600 – 45.200
Percent high school educated	T.I.	2,542	2,542	84.608	6.850	---	53.700 – 97.500
Overall scale							
Cumulative disadvantage	T.I.	2,542	2,542	13.627	4.530	---	4.139 – 33.993
Demographic characteristics							
Law enforcement agencies	T.I.	2,542	2,542	5.703	7.201	---	1.000 – 112.000
Sworn law enforcement officers	T.I.	2,542	2,542	238.929	845.471	---	0.000 – 25,485.000
Rurality	T.I.	2,542	2,542	4.928	2.719	---	1.000 – 9.000
Total population / 10,000	T.I.	2,542	2,542	10.218	30.878	---	0.009 – 984.002
Sex ratio	T.I.	2,542	2,542	100.141	11.000	---	73.400 – 325.000
Age-dependency ratio	T.I.	2,542	2,542	65.072	10.063	---	6.300 – 111.200
Percent White	T.I.	2,542	2,542	85.045	15.991	---	3.552 – 100.000

The primary independent variable for this chapter is lagged general crime. Table 8 shows this ranges from zero to 125,073.000 reported general crimes, with an average of 2,390.854 reported crimes within a county-year. Additional focal independent variables for this chapter are the three specific crime types: crimes against persons (consisting of eight offenses; see Table 2), crimes against property (consisting of nine offenses), and crimes against society (consisting of 11 offenses). Similar to the general crime variable, these variables are lagged by one year. Within the multivariate analysis, these variables were originally treated as individual items. With a close examination of the tolerance statistics, VIFs, and correlations, it was clear these focal independent variables could not exist in a model together. Rather, I first examined the overall general crime variable in a model building process. Then, I examine three additional models each examining a specific type of crime. Throughout the exploration for concerns of multicollinearity, two demographic variables were removed. The population rate was very strongly correlated with the crime variables, so this variable was removed first. There were additional concerns for multicollinearity with the variable measuring the number of law enforcement agencies in the county. This variable was ultimately removed from the primary analysis, but an inclusion of this variable is included in the sensitivity analysis. With the removal of these two demographic variables the tolerance statistics and VIFs reveal no concerns of multicollinearity.

The prior paragraphs discuss the possibility of general crime acting as a significant predictor of police crime. In addition to this, it is necessary to explore police crime acting as a predictor of general crime. This models a very similar relationship. The same social disorganization and demographic characteristics variables are included throughout the analysis. The primary independent variable will now be the lagged police crime variable. These data will now include a police crime variable capturing years 2012-2015 to model general crime from

2013-2016. These data now include an additional year of data for the lagged police crime variable but are still limited based on the years in which the UCR data are available. The data used throughout this chapter are described in the same descriptive table in Chapter VI (see Table 5). These data now include a primary focal independent variable, lagged police crime. This variable is a time-variant measure ranging from zero to 42.000 with a mean value of 0.419 ($SD_{between}$=1.418; SD_{within}=0.842). Tolerance statistics, VIFs, and correlations were again examined using this set of independent variables. Population rate was again strongly correlated with the police crime variable, so the control measure was removed. After this exclusion, there existed no further concerns of multicollinearity.

This chapter uses model-building processes, similar to the prior two analytical chapters. The focal independent variables throughout these models are now time-variant. Mixed-effect models are able to capture within-county and between-county variation. The other variables in the model remain time-invariant. The first two model building processes regress police crime on predictors. The final model building process regresses general crime on predictors. The first models in each of these processes examine the sole effects of the focal independent variable. Additional variables are added to the models throughout the process, similar to the model builds in previous chapters.

The series of mixed-effects models used in this analytical chapter can be expressed with the following formulas:

$$(police\ crime)_{ij} = \beta_0 + \beta_p(TVGCV)_{i(j-1)} + \sum b_q(TISDV)_i + \sum b_q(TICV)_i + \varepsilon_{ij}$$

$$(general\ crime)_{ij} = \beta_0 + \beta_p(TVPCV)_{i(j-1)} + \sum b_q(TISDV)_i + \sum b_q(TICV)_i + \varepsilon_{ij}$$

These formulas represent a mixed-effects model which regresses police crime, or general crime respectively, on time-variant and time-invariant predictors with the inclusion of a time-lagged independent variable. Year *j* is nested in county i. The global constant term across time and counties is represented by the β_0 term. The next term within the formula models the time-lagged general crime variable. In the second formula, this term represents the time-lagged police crime variable. The β_p value within this term represents the fixed-effect coefficient. The $(TVGCV)_{i(j-1)}$ or $(TVPCV)_{i(j-1)}$ terms denote the time-variant general crime or police crime variables, which are lagged by one year (denoted by *j-1*). The remainder of the model is the same format at the previous two analytical chapters with each b_q value indicating the random-effects coefficients. The social disorganization regressors are models by $(TISDV)_i$. The control regressors are modeled by $(TICV)_i$. The final term in the model, ε_{ij}, represents the error term.

Multivariate Results

Regressing police crime on predictors

The mixed-effects models regressing police crime on predictors, including lagged general crime, are reported in Table 9. Throughout the exploratory analysis, the independent variables included throughout the model building process were closely examined for concerns of multicollinearity. Tolerance statistics, VIFs, and correlations reveal no further concerns of multicollinearity. The models reported in Table 9 are multilevel, mixed-effects models with standardized coefficients and bootstrapped standard errors.

Model 1 in Table 9 displays a model that regresses police crime onto the lagged general crime variable. This model reveals that lagged general crime is significantly associated with police crime. This zero-order model suggests there exists a significant, bivariate relationship between lagged general crime and police crime. A positive coefficient indicates that county-years with more general crime (lagged) are likely to also experience more police crime in the following year.

Table 9. Mixed-Effects Models Regressing Police Crime on Predictors; *n*=2,542 Counties.

	Model 1		Model 2		Model 3	
	b_z	BSE	b_z	BSE	b_z	BSE
Focal independent variables						
Lagged general crime (UCR)	.231	.006***	.209	.007***	.187	.007***
Social disorganization variables						
Gini index	--	--	.039	.003***	.035	.003***
Percent owner-occupied housing units	--	--	-.045	.004***	-.030	.004***
Percent vacant housing units	--	--	-.011	.003***	.014	.003***
Cumulative disadvantage	--	--	-.019	.003***	-.030	.004***
Demographic characteristics						
Rurality	--	--	--	--	-.053	.004***
Sex ratio	--	--	--	--	-.017	.002***
Age-dependency ratio	--	--	--	--	-.003	.003
Percent White	--	--	--	--	-.047	.004***
Intercept	.162	.003***	.162	.003***	.164	.003***
Model statistics						
Wald χ^2	1,419.73***		2,553.44***		3,521.17***	
Between cluster SD	.087		.087		.087	
Within cluster SD	.042		.039		.035	

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Additional variables are added throughout the model building process for a more complete analysis. Model 2 in Table 9 adds the social disorganization variables. This model now regresses police crime onto a lagged general crime variable and variables measuring the antecedents of social disorganization. The focal independent variable lagged general crime and all the social disorganization variables are significant. The lagged general crime variable remains positively associated with police crime, indicating that counties with higher counts of general crime are often experiencing high counts of police crime in the subsequent year. The social disorganization variables reveal a complex narrative surrounding police crime. The Gini index variable is positively associated with police crime, meaning higher income inequality is likely to be correlated with police crime. Additionally, the percent of owner-occupied housing units is negatively associated with police crime. This would suggest that counties with more housing units occupied by their owners are likely to be associated with less police crime. The findings from the remaining two social disorganization variables are inconsistent with what the theory would suggest. The cumulative disadvantage and percent vacant housing variables are negatively associated with police crime. This concludes that counties with more vacant housing and more cumulative disadvantage are likely to experience less police crime. These empirical results do not align with the general hypotheses of the current theoretical framework, but still offer valuable insights regarding the relationship between police crime and social disorganization.

The final model displayed in Table 9 includes all previous variables and demographic variables.. Similar to the previous models reported in Table 9, this model was able to explain a significant amount of variation in the police crime measure. In comparison to the prior two models, the final model covers additional variation in the police crime measure. Coupled with the meaningful interpretations of the significant variables, this would suggest that the final model reported in Table 9 is the closest fitting model for explaining variation in police crime throughout the United States. The primary independent variable, lagged general crime, is significantly and positively associated with police crime. Consistent with my hypothesis (H3), this suggests that counties with more general crime are likely to experience more police crime. Similar to the previous model, the social disorganization variables reveal mixed findings. The Gini index, percent owner occupied housing, and percent vacant housing variables conclude results in support of social disorganization theory. The cumulative disadvantage variable is again negatively associated with police crime. These results, coupled with the results from Chapter V, will be discussed in the final chapter of this dissertation to determine the implications of these findings on police crime throughout the United States. Of the demographic variables, the only insignificant predictor is the age-dependency ratio measure. All other demographic variables are significant. The rurality, sex ratio, and percent White variables are negatively associated with police crime. This is consistent with the models from Chapter V which also regress police crime on predictors.

Table 10 explores the different types of general crime as predictors of police crime. These models are aimed at determining whether there is a specific type of general crime responsible for the significant association between general crime and police crime. The types of general crime are broken into three distinct categories: crimes against persons, crimes against property, and crimes against society. A further look at which criminal charges are categorized into which types of crime can be found in Table 2. The models in Table 10 otherwise have the same predictor variables are Table 9. Tolerance statistics, VIFs, and correlations are again examined and there remains no concerns of multicollinearity.

Table 10. Mixed-Effects Models Regressing Police Crime on Predictors; *n*=2,542 Counties.

	Model 1		Model 2		Model 3	
	b_z	BSE	b_z	BSE	b_z	BSE
Focal independent variables						
Lagged crimes against persons (UCR)	.183	.007***	--	--	--	--
Lagged crimes against property (UCR)	--	--	.178	.007***	--	--
Lagged crimes against society (UCR)	--	--	--	--	.187	.006***
Social disorganization variables						
Gini index	.038	.003***	.037	.004***	.034	.003***
Percent owner-occupied housing units	-.029	.004***	-.032	.004***	-.031	.004***
Percent vacant housing units	.013	.003**	.014	.003***	.015	.003***
Cumulative disadvantage	-.036	.004***	-.032	.003***	-.029	.003***
Demographic characteristics						
Rurality	-.056	.004***	-.060	.004***	-.052	.004***
Sex ratio	-.017	.002***	-.016	.002***	-.017	.002***
Age-dependency ratio	-.006	.003*	-.004	.003	-.002	.003
Percent White	-.045	.004***	-.046	.004***	-.049	.003***
Intercept	.164	.003***	.164	.003***	.164	.003***
Model statistics						
Wald χ^2	4,078.79***		3,613.92***		3,654.49***	
Between cluster SD	.087		.087		.087	
Within cluster SD	.035		.037		.035	

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

A model building process was initially explored but reported very similar findings to Table 9. Therefore, the full models for each type of general crime are tabled together in Table 10 for simplicity. Model 1 regresses police crime on crimes against persons and predictors. Model 2 regresses police crime on crimes against property and predictors. Model 3 regresses police crime on crimes against society and predictors. Each type of crime variable is significantly and positively associated with police crime. There is not a specific type of general crime that is able to solely account for the significance of overall general crime. Each type of crime, individually, can be seen as a significant predictor of police crime. The remaining variables in the models reveal very similar findings as the final model in Table 9.

Regressing general crime on predictors

The previous section clearly establishes that lagged general crime is a significant predictor of police crime throughout multivariate analysis. Following these findings, it is essential to also examine if lagged general crime is also significantly associated with police crime. This will provide a more complete understanding of these structural variables.

Table 11 displays the mixed-effects models regressing general crime on predictors, including lagged police crime. Tolerance statistics, VIFs, and correlations are continually explored for concerns of multicollinearity. All tolerance statistics and VIFs satisfy the standard thresholds. The models reported in Table 11 include standardized coefficients and bootstrapped standard errors.

The first model in Table 11 regresses general crime on a lagged police crime variable. This zero-order model identifies a significant, bivariate relationship between lagged police crime and general crime. The relatively small Wald χ^2 will be discussed shortly. This model indicates that lagged police crime is significantly associated with general crime and county-years with

Table 11. Mixed-Effects Models Regressing General Crime on Predictors; *n*=2,511 Counties.

	Model 1		Model 2		Model 3	
	b_z	BSE	b_z	BSE	b_z	BSE
Focal independent variables						
Lagged police crime	.020	.004***	.017	.004***	.001	.003
Social disorganization variables						
Gini index	--	--	.186	.008***	.006	.007
Percent owner-occupied housing units	--	--	-.436	.008***	-.169	.009***
Percent vacant housing units	--	--	-.552	.008***	-.092	.007***
Cumulative disadvantage	--	--	-.137	.009***	.119	.008***
Demographic characteristics						
Law enforcement agencies	--	--	--	--	.477	.007***
Rurality	--	--	--	--	-.631	.010***
Sex ratio	--	--	--	--	-.243	.008***
Age-dependency ratio	--	--	--	--	-.352	.009***
Percent White	--	--	--	--	-.012	.009
Intercept	6.69	.007***	6.67	.006***	6.67	.006***
Model statistics						
Wald χ^2	21.18***		19,388.22***		58,146.14***	
Between cluster SD	.088		.088		.088	
Within cluster SD	2.509		1.851		.887	

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

more police crime are likely to also have more general crime. Coupled with the findings from Tables 9 and 10, this would suggest that lagged police crime may be associated with general crime, just as lagged general crime is associated with police crime. A continued exploration with additional structural level variables is needed before drawing this conclusion.

Model 2 of Table 11 regresses general crime on lagged police crime and social disorganization variables. Lagged police crime remains significant in this model. Again, this would suggest that counties with more police crime are likely to also experience more general crime. The Gini index variable is significant and positively associated with general crime. Counties with higher income inequality are likely to be correlated with higher reports of general crime. The percentage of owner-occupied housing units is significant and negatively associated with general crime. This would suggest that counties with more housing units occupied by owners are more likely to be associated with lower counts of general crime. The cumulative disadvantage and percent vacant housing variables are significantly and negatively associated with general crime. This suggests that counties with less cumulative disadvantage and less vacant housing are likely to experience more general crime. Similar to the model regressing police crime, this reveals mixed support for social disorganization theory.

The final model of Table 11 regresses general crime on the previous variable and demographic variables. With the inclusion of the demographic variables, the Gini index variable is no longer significant. The variables measuring the percent of owner-occupied housing units and percent vacant housing remain significant and negatively associated with general crime. The cumulative disadvantage variable is now significant and positively associated with general crime. All demographic variables are significant beside the percent White variable. The most prominent result from Model 3 is the insignificance of the lagged police crime variable. This indicates that with the inclusion of the demographic variables, lagged police crime is no longer significantly associated with general crime. Empirically, lagged police crime does not share a robust, significant relationship with general crime. The previous significant relationship may be better explained by a confounding variable included in the final model.

Looking at the models reported in Table 11, it is evident that the Wald χ^2 is relatively small in Model 1, compared to Models 2 and 3. This would suggest that despite being significant, Model 1 fails to explain much variation in the dependent variable in comparison to Models 2 and 3. The implications of these findings will be further discussed in the final chapter of this dissertation.

Sensitivity Analysis

Table 9 regresses police crime on predictors, with bootstrapped standard errors. These same models are displayed in Appendix F, without bootstrapping. The re-estimated models in Appendix F remain significant with very minimal differences in comparison to Table 9. These re-estimated findings confirm the robustness of the results reported throughout this chapter. During the analytical approach section of this chapter, it was reported that the number of police agencies variable was removed from analysis due to concerns of multicollinearity. The VIF for this variable was 2.5 with a tolerance statistic of 1.58. This teeters right at the standard threshold for concerns of multicollinearity. This variable was also explored for inclusion and minimal differences were ultimately found. For simplicity, this variable was not reported throughout the models.

Appendix G re-estimates the models from Table 10, now without the bootstrapped standard errors. These re-estimated models remain significant with very minimal differences.

Each type of general crime remains significantly and positively associated with police crime. Again, this displays the robustness of the results reported in Table 10.

Table 11 regresses general crime on predictors, with bootstrapped standard errors. Each of these models are re-estimated without bootstrapping and reported in Appendix H. The models in Appendix H are very similar to the model originally reported in the chapter. The final model confirms that lagged police crime is not a significant predictor of general crime. This confirms the findings reported throughout this chapter.

CHAPTER VIII. DICUSSION AND CONCLUSION

American policing currently faces polarizing debates concerning accountability and integrity. Existing literature has studied the decades old patterns of police misconduct through a theoretical lens (e.g. Donner et al., 2021; Fyfe & Kane, 2006; Kane & White, 2012; LaFree, 2021; Stinson, 2020). Individual level criminological theories focus on the individual characteristics of the police officers and how these attributes may be associated with police crime. Researchers have explored gender, educational attainment, race, and other individual level characteristics to potentially explain the variation in police crime (see Fyfe & Kane, 2006; Gaub, 2020; Hong, 2017; White & Kane, 2013). Furthermore, prior literature has examined how stressors and factors unique to the law enforcement profession may impact the likelihood of officers committing crime or misconduct (see Arter, 2007; Bishopp et al., 2016; Kurtz et al., 2015; Stinson, 2020). While there has been a clear acknowledgement that a more macro approach should also be examined (Donner et al., 2021), few existing studies have been able to quantitatively study police crime from a structural perspective.

This dissertation aimed to build on the existing studies of police crime to gain a more comprehensive and empirically based structural understanding of police crime throughout the United States. Informing scholars and policy makers about the implications of structural factors on police crime is important because these findings can directly impact the safety of American communities. The goal of this dissertation is to improve American policing by informing evidence-based policies rooted in a structural sociological perspective. This chapter will conclude with policy recommendations aimed at achieving this goal.

This dissertation was constructed into three analytical chapters. Each analytical chapter answered a research question designed to further the understanding of American police crime from a structural perspective. To effectively answer these research questions, I constructed a nationwide, longitudinal panel dataset of American counties including variables on police crime, general crime, the antecedents of social disorganization, and other county level variables. Each analytical chapter reported findings regarding the specific research question, but the totality of these findings achieved a more comprehensive story. First, this concluding chapter will discuss the individual findings revealed by each analytical chapter. Second, this chapter will discuss the implications of these findings altogether and provide empirically based policy recommendations. Third, this chapter will discuss the limitations of this research and provide fellow researchers directions for future research.

Research Question 1

The first analytical chapter (see Chapter V) explored the structural factors associated with police crime. The research question that guided this chapter inquired about the significant county level correlates of police crime (RQ1). Based on social disorganization theory, I hypothesized that the proxy measures of social disorganization would be associated with the measure of police crime (H1). Moreover, I suggested that counties with higher levels of social disorganization would likely experience more police crime. To explore this research question, I employed multilevel regression models regressing police crime on county level predictors. The dependent variable for this analytical chapter was a longitudinal measure of police crime from years 2013 through 2017. An exploration of these regression models uncovered a complex relationship between social disorganization and police crime.

The progression of models reported in Table 4 allowed the ability to observe the results as more variables were added into the models regressing police crime. The first model displayed significance for all social disorganization variables. This finding suggests there is a statistically significant association between police crime and social disorganization, disregarding other county level factors. As additional variables were added into the model, these significant associations remain. This showed that antecedents of social disorganization continue to have a significant relationship with police crime while accounting for several county level demographic variables.

The final model revealed statistically significant correlations between the social disorganization variables and police crime. Despite observing significance, the findings provided mixed evidence for my hypothesis (H1). The variables capturing Gini index and percent of vacant housing units are significantly and positively associated with police crime. The variable measuring the percent of owner-occupied housing units is significantly and negatively associated with police crime. These findings provided support for my hypothesis (H1) and suggest that counties that are more socially disorganized may experience higher counts of police crime. Conversely, I found mixed results that do not support my hypothesis (H1). The constructed cumulative disadvantage variable was significantly and negatively associated with police crime. This is a scale capturing educational attainment (reverse coded), poverty, rates of uninsured, and unemployment rates on a county level. This result suggested that counties with more cumulative disadvantage, a proxy measure of social disorganization, would likely experience less police crime. In conclusion, these results revealed mixed evidence for my first hypothesis (H1).

The model building process also revealed a unique behavior of one of the social disorganization variables. In the first and second regression models (see Table 4), the percent of vacant housing units variable was significantly and negatively associated with police crime. In the final model when all demographic variables are included, this variable remains significant but flips direction. The coefficient switching from negative to positive suggests this variable may not be a stable predictor and is likely affected by one of the demographic variables that was added into the model. After extensive exploration of these variables, additional regression models with interaction terms suggest there could be suppressed moderation occurring within the models reported in Table 4. This would mean that one, or multiple, of the demographic variables are able to significantly alter the direction or strength of the association between police crime and the percent vacant housing variable. An exploration of the multicollinearity statistics and correlations between the independent variables confirms there are no concerns of interdependency between predictor variables. This behavior should be noted as a unique characteristic of these models but should not interfere with the interpretation of the findings. I would suggest fellow researchers to be aware of the potential suppressed moderation with these data and to continue exploration for additional insights.

The results from the regression models suggest mixed support for my first hypothesis (H1). There does appear to be statistical significance associated with the social disorganization variables, but the directions of association remain contradictory. Furthermore, a continued exploration of these variables throughout the other two analytical chapters further deepens the complexity of these associations.

Research Question 2

The second analytical chapter approached the constructed dataset with a similar analytical strategy, now examining general crime as the primary dependent variable. This variable measured the general crime of American counties in years 2013 through 2016. The research question that guided this statistical analysis asked about the significant correlates of general crime on a structural level and the comparison to the structural correlates of police crime (RQ2). The analytical strategy used to examine this research question was two-fold. First, I regressed general crime onto the same predictors as the first analytical chapter. These predictors included social disorganization variables and several county level demographic variables. Second, I examined and compared the results of the regression models regressing police crime and general crime. I hypothesized that I would find support for social disorganization theory and my proxy measures of social disorganization would be significantly associated with general crime (H2).

Table 6 reports the model building process regressing general crime on predictor variables. The first analytical model revealed statistical significance associated with each social disorganization variable. This would suggest that social disorganization and general crime have a significant relationship. In the final analytical model, the statistical significance remains for the percent owner-occupied housing units, percent vacant housing units, and cumulative disadvantage variables. With all the demographic variables included in the model, the Gini index variable is no longer significant. This would suggest that one, or multiple, of the demographic variables are able to explain the variation associated with the earlier significance of this variable. Similar to the first analytical chapter, there was a unique finding regarding the direction of one of the social disorganization variables.

These regression models revealed that the social disorganization variables and general crime are significantly correlated. This would support the hypothesis (H2). Despite the Gini index variable being insignificant, the percent of owner-occupied housing units and cumulative disadvantage variables are statistically significant, in the direction I hypothesized. The percent of vacant housing units variable is significant and in the opposite direction than hypothesized. This regression model suggests that counties with more vacant housing are likely to experience less general crime. The contradictory directions of significance conclude mixed results for my second hypothesis (H2).

Similar to the police crime models, the general crime models showcased some perplexing behavior worthy of discussion. To my knowledge, this dissertation is the first quantitative study to explore county level police crime on a national scale. This is the first exploration of the constructed dataset and is likely the first time these data were explored altogether in a quantitative study. With this, it was expected to discover some otherwise unknown results. As more empirical studies explore police crime from a structural perspective, it is my hope that these results can be clarified. Similar to the police crime model, there appears to be additional suppressed moderation in the general crime model. Again, it was confirmed through multicollinearity statistics and correlations that there are no concerns of interdependency between predictor variables. These unique results suggest the need for further exploration. Furthermore, the general crime models produced exceptionally large Wald χ^2 values. A detailed discussion about the Wald χ^2 values is included in the following section of this chapter. Unexpected results like these are anticipated when working with a newly constructed dataset. With continued research and exploration of these data, it is my hope that these data can progress the field of criminology to a more complete understanding of police crime through a structural perspective.

The results from the analytical models regressing police crime and general crime were compared for a thorough understanding of the similarities and differences. A Clogg test was used to compare the statistical equality of coefficients between the regression models. Despite my hypothesis suggesting the similarities between the models, this is far from the actual results. There was not a variable in the models that did not significantly differ between the police crime and general crime models. The only social disorganization variable that was significant in both models and in the same direction was the percent of owner-occupied housing units variable. These coefficients still significantly differed in magnitude. The Gini index variable was significant in the police crime model but insignificant in the general crime model. The percent of vacant housing and cumulative disadvantage variables were significant in both models but in opposite directions. It is important to recognize the statistical differences between the measures associated with general crime and police crime. The variables associated with police crime are glaringly different than the associations with general crime. This is important to recognize because policies focused solely on police crime may inadvertently be affecting general crime and vice versa.

Police crime and general crime do not exist in a vacuum. American communities are faced with these types of crime simultaneously. As suggested in the first two analytical chapters of this dissertation, it is likely that police crime and general crime share a complex interrelated relationship. The last analytical chapter of this dissertation investigated this likely interwoven relationship.

Research Question 3

The previously discussed analytical findings of this dissertation examined police crime and general crime separately. This strategy allowed for the comparison of models and individually identified the correlates of both general crime and police crime. While this analytical approach was useful for a basic structural understanding of police crime, it should be noted that police crime and general crime do not exist isolated from one another. It is likely there exists an interwoven relationship between police crime and general crime.

The third and final analytical chapter examined police crime and general crime simultaneously. The third research question investigated if there was a significant relationship between general crime and police crime at a structural level (RQ3). Multilevel regression models were used to explore this relationship. The first set of models regressed police crime on lagged general crime, social disorganization variables, and demographic variables. These models are aimed at determining if general crime is a significant predictor of police crime. While police crime is my primary dependent variable for the third analytical chapter, it was also important to determine if the interwoven relationship was contingent on the time-ordering of the variables. Therefore, I also explored whether lagged police crime was a significant correlate of general crime. This exploration was done with an additional set of regression models that regressed general crime on lagged police crime, social disorganization variables, and demographic variables. I hypothesized that there would be a significant relationship between general crime and police crime (H3). Furthermore, I hypothesized that counties with more general crime would likely experience more police crime.

The first model building process aimed at answering the third research question regressed police crime on lagged general crime and other predictors. These models (see Table 9) are similar to the models in Chapter V (see Table 4) that regressed police crime on county level predictors. Lagged general crime was a significant, positive predictor of police crime. The social disorganization variables remain significant in these models. Therefore, while accounting for lagged general crime, the social disorganization variables still have significant main effects associated with police crime. These findings support my hypothesis (H3) and suggest there is a significant relationship between general crime and police crime.

The second set of models in Chapter VII separated general crime into three distinct types of crime: crimes against persons, crimes against property, and crimes against society. Police crime was then regressed onto these lagged types of general crime, individually. These models determined if there was a specific type of general crime responsible for the significant main effect of general crime. These models produced anticlimactic results. Each type of general crime was significantly associated with police crime, with no stark differences in models. These results are important because they suggest that all types of general crime are significantly associated with police crime, and it is not one specific type of general crime that is responsible for this significant relationship.

The third and final set of models from the final analytical chapter regressed general crime on a lagged police crime variable. Prior models regressing police crime on lagged general crime demonstrate there exists a relationship between general crime and police crime. This final set of models was used to further observe the potential directions of this relationship. It is important to recognize these regression models are unable to determine causality. However, these models are able to generally examine the direction of the relationships among the properly time-ordered variables such as general crime (t) and lagged police crime (t-1) or police crime (t) and lagged general crime (t-1).

In these models, the relationship between general crime and lagged police crime was significant when lagged police crime was the sole predictor variable. In the final model with all demographic variables, the lagged police crime variable was no longer significant. This would suggest that one, or multiple, of the demographic variables was able to effectively explain the variation associated with the lagged police crime variable. In this final model, lagged police crime did not act as a significant predictor of general crime. These findings led to the conclusion that the interwoven relationship between general crime and police crime may be contingent on the time-ordering of the variables. This finding is meaningful because it allows researchers to further recognize how policies involving general crime may inadvertently be also impacting police crime.

The analytical models regressing general crime on predictors, specifically in Table 11, produced unexpected model statistics. These unusual statistics called for further exploration into what this may mean with respect to my results. The Wald χ^2 model statistic determines whether the independent variables are able to collectively produce a significant model regressing the dependent variable (see Wald, 1943). Statistically, this is measuring whether the combination of coefficients for the model are collectively different than zero. The null hypothesis for this statistical test states that the coefficients for all independent variables are equal to zero (Harrell, 2015). Models with even just one extremely powerful independent variable can be deemed significant and reject the null hypothesis, because statistically it would be highly unlikely for that coefficient to equal zero.

The models that regress general crime on predictors have exceptionally high model statistics in comparison to the models that regress police crime. This can first be seen in the comparison of models from Chapters V and VI. Despite all models being significant, the comparison in the magnitude of Wald χ^2 values suggests the need for a further examination of the standardized coefficients. As shown in Table 4 with the models regressing police crime, the significant standardized coefficients are relatively small, ranging from 0.015 to 0.154 in Model 3. Larger standardized coefficients indicate more powerful predictors. Although some variables are more powerful than others, it does appear that this model is somewhat balanced in terms of the power of the predictors. Table 6 tells a different story with models regressing general crime.

Again, all models in Table 6 are significant but the model statistics are exceptionally large. The significant standardized coefficients range from 0.067 to 0.626 in Model 3. The larger standardized coefficients reveal the variables that are very powerful predictors of general crime. It would be very unlikely that these coefficients are equal to zero, firmly rejecting the null hypothesis and producing a large Wald χ^2 model statistic value.

The final models of this dissertation regress general crime on predictors including a focal independent variable of lagged police crime. These models are significant with exceptionally large Wald χ^2 model statistic values (see Table 11). The significant predictors in Model 3 have standardized coefficients reaching as high as 0.631. This variable alone might explain the rejection of the null hypothesis and considerably high model statistic value. The model build in Table 11 is particularly interesting because of the juxtaposition between the model statistics in Model 1 and Models 2 or 3. Model 1 has a relatively low Wald χ^2 value. This model has one independent variable, lagged police crime. The standardized coefficient for this variable is 0.020. In comparison to standardized coefficients in Models 2 and 3, this coefficient is relatively small and close to zero. In Model 1, this variable is the only measure contributing to the overall model statistic. Furthermore, if this coefficient is close enough to zero, it is likely that the model statistic may not be significant, failing to reject the null hypothesis. Model 1 is significant, and the null hypothesis is rejected. This relatively small model statistic suggests that the model may not be as powerful as Models 2 or 3, despite all models being significant. These findings suggest that despite lagged police crime being a significant predictor of general crime in Model 1 of Table 11, this model does not explain a comparable amount of variation compared to Model 3. Therefore, it can be concluded that Model 3 in Table 11 is a better fit and explains more variation in general crime.

In summary, lagged police crime was not significantly associated with general crime despite lagged general crime being significantly associated with police crime. This seemingly basic finding greatly progresses the structural understanding of police crime throughout the United States by revealing the interwoven relationship between general crime and police crime. Substantively, this means that police crime may not be able to be isolated from general crime in many counties throughout the United States. This dissertation concludes the most accurate way to explore police crime from a structural perspective is to examine police crime in unison with general crime. The implications associated with this finding can be translated into meaningful policy recommendations.

Policy Recommendations

The purpose of this dissertation is to advance the field of criminology by developing a more comprehensive understanding of police crime from a structural perspective. This nationwide quantitative study revealed otherwise unknown empirical findings about American police crime. Through a theoretical lens, these findings can be used to inform meaningful implications. Well-informed, data-driven policy recommendations based on the findings of this dissertation will hopefully improve American policing by addressing police crime from a structural perspective.

Review of current policy literature

The existing policy literature aimed at reducing police crime often takes an individual or agency level approach. Law enforcement departments may be able to effectively enforce these policies (Eitle et al., 2014), whereas any policies focused on environmental or more macro elements could be more difficult to execute. Prior to discussing the policy recommendations informed by this dissertation, it is important to review the current policy recommendations existing in literature.

Individual level policies focused on reducing police crime are largely concentrated on the recruitment and hiring practices of law enforcement officers. Researchers have suggested efforts of hiring more women (Gaub, 2020), hiring more LGBTQ+ officers (*Principles of Promoting Police Integrity*, 2001), or hiring more officers of racial or ethnic minorities (Hong, 2017). Additionally, screening tools have been suggested to identify candidates with low levels of self-control (White & Kane, 2013). Beyond recruitment and hiring policy recommendations, current literature suggests policy recommendations aimed at the retention of good officers. These recommendations include continued education and training of law enforcement officers (President's Task Force on 21st Century Policing, 2015). Additional policies suggest the need for competitive pay, education incentives, and opportunities of career growth to retain high-quality law enforcement officers (Wilson, 2012; Wilson & Grammich, 2009). Agencies should adopt a zero-tolerance approach to harassment in the workplace and have clear, written policies regarding workplace complaints (*Principles of Promoting Police Integrity*, 2001). These efforts are contingent on the ability of agencies to access necessary resources to implement these recommendations (*Principles of Promoting Police Integrity*, 2001; Wilson, 2012).

Current literature also provides agency level policy recommendations aimed at identifying and deterring police misconduct and police crime. The most general policy recommendation repeatedly found in existing literature is the need for direct internal policies about police misconduct (Hassell, 2016; President's Task Force on 21st Century Policing, 2015; Walker & Archbold, 2014; Walker & Macdonald, 2009). This includes written policies about fair supervision of officers, administrative oversight, internal affairs procedures, transparency surrounding use of force policies, and policies regarding the accountability of departments and individual officers. Broad, indirect policies have been suggested about the need to change departmental cultures (Hassell, 2016; President's Task Force on 21st Century Policing, 2015). Understandably, these policies are much more difficult to execute and would take collective support to effectively be enforced.

Individual and agency level policy recommendations are the focus of current police policy literature. These policies can often be enforced by departments and have clear, actionable items to implement. Despite the ease of these policies, these recommendations may be incomplete because they fail to account for the structural level factors associated with police crime. Researchers have acknowledged that individual and agency level factors cannot solely explain police misconduct and police crime (Donner et al., 2021). The need for a structural perspective on police crime policies has been suggested (Eitle et al., 2014).

The structure of American policing may hinder the effectiveness of implementing policy recommendations. A lack of centralized policing practices has produced a myriad of policies regarding American policing. There are over 18,000 law enforcement agencies across the United States, each with their own policies and procedures (*Crime/Law Enforcement Stats (Uniform Crime Reporting Program)*, n.d.). The current policies aimed at reducing police crime throughout the United States are often up to the individual police chiefs or administrators of the individual departments. To my knowledge, very few studies have quantitatively researched police crime on a large scale, making it difficult to provide empirically based policy recommendations across multiple jurisdictions. Despite nationwide initiatives promoting "community policing," the priorities of many agencies across the nation may still fail to prioritize the betterment of the local communities (Hassell, 2016; President's Task Force on 21st Century Policing, 2015).

The decentralized nature of the American policing system has been at the forefront of discussion when considering policies from a structural perspective. There has been a call for more equitable policies and procedures for policing throughout the United States (Hassell, 2016). The discretionary nature of American policing has also consistently been a factor of discussion in current policing literature. Smith brings to light the need for any discretionary behavior by police to be examined through a lens of neighborhood contexts (Smith, 1986). Any discretionary police behaviors cannot be isolated from the environment in which they took place. This brings up concerns for the suggestions of more centralized police policies and procedures. These perspectives seem to offer contradictory stances.

From a social disorganization perspective, Kane offered a direct policy recommendation that could be carried out by community leaders or law enforcement officials. This policy recommendation acknowledged the difference in neighborhood contexts but also recognized the difficulty in implementing widespread policy. He suggested that there should be an assigned rank to communities based on the predicted levels of police misconduct (Kane, 2002). Kane broadly discussed that the risk factors that should be considered when assigning this rank are population mobility, structural disadvantage, and percent Latino population (Kane, 2002). These risk factors could be discussed and prioritized within the local communities. This rank could then be subsequently used to inform and educate law enforcement officers, community leaders, and community members.

The current body of literature aimed at reducing police crime may fall short of finding a resolution for this national crisis. The policies focused on individual and agency factors could be seen as incomplete because they often fail to acknowledge the structural level correlates. The recommendations from this dissertation are intended to supplement these policies and build on the existing literature, which calls for the need for more policies focused on macro findings. The findings from this project inform three policy recommendations rooted in a structural perspective aimed at reducing police crime throughout the United States. It is my hope that these policy recommendations offer clear insights for police officials and community leaders to encourage effective change.

Policy recommendation 1: Identify vulnerable communities

The first policy recommendation based on the findings of this project is an expansion of Kane's work (see Kane, 2002). Kane suggested that communities are assigned a rank based upon a predicted level of police crime (Kane, 2002). He identified risk factors that should be considered when assigning these ranks, but this discussion offers additional insights. This policy recommendation is intended to identify communities vulnerable to police crime so community stakeholders can bolster the community with information, education, and additional resources, if available.

This dissertation identified county level correlates of police crime. This means that the significant variables identified are likely to be associated with more or less police crime within counties based upon the direction of the coefficient. An examination of Table 9 identifies which variables could be included in developing a rank of vulnerability.

First and foremost, this dissertation clearly identified the interwoven relationship between police crime and general crime. The significant correlation between lagged general crime and police crime suggests that counties with high counts of general crime are likely to experience high counts of police crime in the subsequent year. Of all the significant correlates to police crime, lagged general crime has the largest standardized coefficient. This would indicate that compared to all the significant correlates, the measure of lagged general crime has the strongest correlation with police crime. It should be clearly noted that this dissertation does not have the ability to determine causation, but rather correlation. When assigning a rank of vulnerability to a community, a measure of general crime from the prior year should hold significant weight. This risk factor alone should be a clear indication to community stakeholders that their community may be vulnerable to police crime.

Furthermore, police crime and additional county level characteristics were found to have statistically significant relationships. The findings of this dissertation revealed that counties with higher levels of income inequality (measured by the Gini index) and higher percents of vacant housing are likely to experience more police crime. Similarly, counties with smaller percents of owner-occupied housing units are likely to experience more police crime. These county level factors should also be considered when determining the vulnerability rank for communities.

Despite being created through a structural lens, this policy recommendation can be implemented on a small scale. There is no need for an entire state, region, or nation to be on board in order to adopt this initiative. This recommendation can be applied to just one local community, a collection of communities, or the entire nation. This policy can be carried out by local community leaders, a group of community advocates, or law enforcement officials. It is my hope that this policy recommendation is accessible to all willing stakeholders.

Policy recommendation 2: Supplement agency-led policies with communitywide initiatives

Most policies aimed at combating police crime have been focused on strategies led by police agencies themselves (Eitle et al., 2014). The second policy recommendation informed by the results of this dissertation suggests the implementation of communitywide initiatives, in addition to the policies carried out by law enforcement agencies. Findings from this dissertation suggest that broad community level policies led by governmental entities or non-profit organizations could also be fruitful at reducing police crime. While agency-led policies may be more straightforward to implement, they may fail to comprehensively address the significant structural correlates of police crime within local jurisdictions. More specifically, policies aimed at reducing police crime while disregarding county level factors may have consequential implications for the communities that these agencies serve.

Regardless of policies focused on hiring practices, continued training, and educational resources for law enforcement, there still exists structural level factors associated with police crime. The results of this project suggest that effective and comprehensive policies may not need to rely solely on agency-led strategies. Communitywide initiatives could supplement the efforts made by law enforcement agencies to reduce police crime.

Current policy literature explores several agency-led policy recommendations, while this dissertation adds to the current discussion by suggesting communitywide initiatives. To redirect the focus to structural level factors, it is important to consider data-driven theoretical perspectives. While this dissertation found mixed empirical support for social disorganization theory explaining police crime, it also revealed a strong correlation between lagged general crime and police crime. This would suggest that reducing general crime within a county would likely also reduce police crime. Furthermore, this suggests that solely focusing time, money, and resources on agency-led policies may be lacking the structural perspective needed to achieve a comprehensive solution. Rather, if efforts were additionally focused on communitywide initiatives to reduce general crime (such as community-focused policing or systems to support mental health crises), this would likely inadvertently reduce police crime. It is clear this dissertation does not provide a comprehensive solution for reducing general crime, but this project reveals complementary avenues for reducing police crime to the established agency-led policies. Governmental entities and non-profit organizations should consider allocating their resources to communitywide initiatives in efforts of taking a supplementary approach to reducing police crime.

Policy recommendation 3: Law enforcement agencies should be active participants in research

The first two policy recommendations are guided by the specific empirical findings of this dissertation. The interwoven relationship between general crime and police crime was established by research focusing on the advancement of the structural understanding of police crime. This otherwise unknown relationship between general crime and police crime was revealed through quantitative research. This relationship, as well as the relationships between police crime and other significant county level factors, has informed the policy recommendations aimed at improving American policing. This dissertation is an example that quantitative research can advance the existing knowledge on a decades-old national crisis. The third and final policy recommendation of this dissertation suggests that law enforcement agencies should engage in meaningful, data-driven research opportunities.

The early stages of this dissertation confronted the scarcity of widespread, existing data about police misconduct or police crime throughout the United States. The process of obtaining data measuring police crime was not through willing participants of law enforcement agencies, but rather through a dedicated scholar with goals of informing the public and improving American policing (see Stinson, 2023). This project would not have been possible without these data. The findings and policy recommendations from this dissertation suggest that law enforcement agencies should not tackle this crisis on their own.

The existing literature surrounding American policing confronts the need for meaningful change. It appears to be instinctual to put a band-aid on a bullet hole, rather than confront the issues with empirically based knowledge and solutions. Agency leaders can fire the "bad apples," require more education, or implement bias training, but these solutions may not be complete and may not offer a comprehensive solution to reducing police crime. Policy makers have systemically overlooked the structural level factors associated with police crime, assumingly unbeknownst to them.

Law enforcement agencies should be active participants in research aimed at finding data-driven solutions to this nationwide crisis. Data collection would be the first step. Law enforcement agencies could regularly collect data about their officers and their behaviors. Departments can help researchers by collecting and disseminating data about officer and departmental demographics. Additional data could be collected and shared about calls for service, use of force, and officer duties. Data about internal complaints, citizen complaints, and the discipline of officers would be essential for studying police misconduct. The collection and dissemination of data is fundamental for progressing this field of research.

With widespread, longitudinal data, scholars can more comprehensively understand a phenomenon. These data could be used to identify trends, recognize descriptive patterns, and provide their communities with regular reports about their officers and their actions. In more advanced applications, these data could be used to determine if there exist statistical differences. Furthermore, inferential statistics can be used to determine relationships between police behaviors and several community factors, just as this dissertation completed. The knowledge and results from the statistical analysis of these data will advance our communities in ways otherwise unachievable. It may be in the law enforcement agencies' best interest to engage with quantitative research by collecting and disseminating data.

By being active participants in research, law enforcement agencies can showcase their readiness to adapt informed data-driven solutions and be an active part of improving American policing for all. The discussions surrounding American policing today are often polarizing and unproductive. Engaging in scholarly research in hopes of identifying empirical resolutions will ideally lead to productive and informed discussions.

Limitations

Despite advancing the structural understanding of police crime, this dissertation is not without limitations. The limitations of this project can be divided into two main categories, theoretical limitations and data limitations.

Theoretical limitations

The primary theoretical framework that guided my hypotheses was social disorganization theory. This theory posits that united communities possess the ability to resist crime and socially disorganized communities lose their ability to control their populations (Shaw & McKay, 1942). To adequately test social disorganization theory, each element of the theory should be individually measured and examined. This dissertation lacked the ability to capture every tenet of social disorganization theory, meaning this project only offers a partial test of the hypotheses of the theory. This dissertation used variables such as percent vacant housing, unemployment rates, and the Gini index to serve as proxy measures of social disorganization. These variables instead capture the precursors of social disorganization. These community characteristics are likely the attributes of a community that is socially disorganized but in no way do they actually measure the social organization of the population.

Furthermore, this dissertation lacked the ability to measure the lack of control within a community. Social disorganization theory suggests that socially disorganized communities lack control and this is the sequential factor that then increases crime and delinquency (Shaw & McKay, 1942). The measures used throughout this dissertation do not possess the ability to capture this element of social disorganization theory. Again, the measures used in this project measure the antecedents of social disorganization. These measures are imperfect at best and scholars should be cautious when interpreting the implications of these variables. Despite these limitations, the data available for the project are still able to produce meaningful and important results regarding police crime and social disorganization theory. Future research should continue to strategize ways to capture the elements of social disorganization theory with the data available to them.

Social disorganization theory is built on the premise that united communities can resist crime (Shaw & McKay, 1942). Applications of this theory often rely on geographic boundaries to capture the concept of community. Prior applications of this theory have used neighborhoods (Lei & Beach, 2020; Sampson, 2012; Smith, 1986), precincts (Kane, 2002), or smaller geographic units a proxies for communities (Sampson & Groves, 1989). This project uses county or county equivalents as a proxy measure of communities. It should be noted that American counties are administratively drawn and are not precise, uniform units (*Substantial Changes to Counties and County Equivalent Entities: 1970-Present*, 2023; United States Census Bureau, 2010; United States Department of Commerce, 1994). American counties are diverse entities characterized by large within unit variation across key demographic and social factors (Hobbs, 1994; United States Census Bureau, 2023). While county boundaries are still likely meaningful, analyses of county level data may not be fully capturing the intended elements of communities as laid out by social disorganization theory.

Data limitations

The data used for this project were secondary data. I was not the primary entity who collected these data, nor did I participate in the creation of the methodologies used to collect the data. Secondary data analysis presents unique challenges for those who analyze and interpret the data. Although the data may not be perfectly curated to answer the research questions presented, available secondary data can still be insurmountably useful for researchers. The prior section discussed the primary concerns with the ACS data used as a proxy measure of social disorganization. This section continues to discuss the data limitations of the remaining data sources.

The CSLLEA and Department of Agriculture data were used primarily for a limited purpose. The CSLLEA data served as a count of law enforcement agencies throughout the United States. Despite being labeled a census, it is within reason to assume the CSLLEA did not capture all law enforcement agencies throughout the United States. Furthermore, the estimates provided by the CSLLEA are likely to regularly change over time. This would suggest that the estimates used from the CSLLEA are just a snapshot of data. Future research should consider using multiple waves of the CSLLEA to provide the ability to measure change over time. The Department of Agriculture data provided an estimate of rurality of American counties. While this variable served its intended purpose as a control measure, a more comprehensive measure of population density and characteristics of rural communities could be explored.

Data from the UCR were used to provide a measure of general crime throughout the United States for study years. While these data were able to provide a longitudinal, national measure of crime, they are not without limitations. First, the UCR program is voluntary. Not all law enforcement agencies reported their crime data to the UCR. This presents a coverage bias issue which was previously discussed in Chapter IV. This dissertation constructed a measure to limit the coverage bias issue by using a CSLLEA measure of number of law enforcement agencies to determine an estimated percent of agencies that reported in each county. Although this is an imperfect solution, it is likely to reduce the larger coverage bias issue. Furthermore, crime data are flawed. The data from the UCR are sourced from law enforcement agencies. These data only capture the crimes in which the perpetrator was caught by law enforcement. Future research should examine other crime data options to further explore the relationship between general crime and police crime.

The data from the Henry A. Wallace Police Crime Database lacks the ability to capture all police crime. The methodology for collecting these data was reliant on the publicly available news coverage of criminal arrests of law enforcement officers. It has been found that this data collection method was able to identify police crime cases otherwise unattainable through alternate methods (Payne, 2013). It is reasonable to assume there may exist a selection and coverage bias issue associated with these data. Furthermore, for the purpose of this study, these data were aggregated into a longitudinal, county level, panel measure of police crime. The individual or agency characteristics associated with these data were not included due to the scope of this project. Lastly, these data are limited to incidents in which a nonfederal law enforcement officer was criminally charged. There exist prominent debates on whether law enforcement officers are held accountable for their actions and this dissertation is not able to contribute to this conversation. The police crime data used throughout this dissertation were limited to cases in which there existed probable cause to arrest the individual, but the determination of this probable cause was not examined. This methodology limits the discretion needed by researchers to classify an action as misconduct, unjustified, or criminal. This methodology is able to reduce the subjectivity of this field of research and objectively rely on law enforcement, prosecutors, and judges to determine arrests and prosecutions. While these data are not perfect, it should be acknowledged that the Henry A. Wallace Police Crime Database is the only longitudinal, nationwide dataset available for examining police crime throughout the United States, to the best of my knowledge. These data have been instrumental in the advancement of this field.

Lastly, the statistical approach lacked the ability to determine causality. As a result, the findings reported throughout this dissertation should be interpreted with the understanding that these statistical strategies merely examine the relationships between these variables. Many of the variables used throughout this project were time-invariant and lacked the ability to examine change over time. The statistical strategies used throughout this dissertation are limited based on the time-order of the variables. Despite these limitations, this dissertation reveals an overwhelming amount of information about police crime from a structural perspective throughout the United States.

Directions for Future Research

In addition to advancing the structural level understanding of police crime throughout the United States, this project also introduces many additional avenues of future research. First, this dissertation broadly reports mixed empirical support for social disorganization theory as it applies to police crime throughout the United States. Though social disorganization theory is a valid conceptual explanation for American police crime, the specific elements of this theory appear to be receiving mixed empirical support. A more thorough examination of specific theoretical concepts, such as social control or collective efficacy, may further advance our understanding of the empirical validity of social disorganization theory as it applies to crimes committed by police officers. Future studies utilizing a social disorganization framework to examine police crime would be invaluable, especially in the context of the concepts of social control and collective efficacy (which were not captured in this project).

Second, this dissertation broaches the gate for new ways of thinking about data infrastructure when studying American police crime. The data used for this project are unique in the way that they were utilized, thereby widening options for future studies on structural level correlates of police crime. The data are primed for use to address research questions that have been otherwise unanswerable with previously existing data infrastructures. While this is important for advancing the current field of research, it also speaks to the need for scientists to continue expanding data capacities to other avenues of investigation related to police crime. Since there are many other publicly available, nationwide, county level datasets that could potentially be merged in a similar way, numerous possibilities for future research remain.

Lastly, racialized tensions in interactions between citizens and police have received extensive media coverage in the last several years. Researchers using a similar data infrastructure could explore how race and ethnicity factor into inequalities among police-citizen relations, police crime, and general crime. The ACS has publicly available, nationwide data on the ethnic and racial makeups of American counties. These data could be merged to the newly constructed dataset: This would allow researchers to study police crime from a structural perspective with a keen eye towards racial dynamics.

Conclusion

Using a theoretical framework and quantitative approach, the purpose of this dissertation was to expand the viewpoint of the significant correlates of police crime by using a structural perspective. Derived from an analysis of a longitudinal nationwide panel dataset of American counties, the findings of this dissertation revealed that there are county level correlates of police crime. While the theoretical framework offered meaningful interpretations of these structural findings, the most notable finding is that crime in the population generally is significantly associated with crime committed by law enforcement officers. Furthermore, this significant relationship is not specifically contingent on the general public committing crimes against persons, crimes against property, nor crimes against society, but rather each general crime type yields significance on its own. Due to the interlinked nature of police crime and general crime, current policies aimed at reducing police crime may be imperfect if they fail to account for these significant structural correlates. This dissertation offers supplemental solutions for reducing police crime and improving American policing by suggesting policies that are simultaneously combatting general crime. The installation of comprehensive policies and practices that address both police crime and general crime appear necessary to reduce the amount of crime committed by law enforcement officers in United States. If found to be effective, a widespread adoption of these policies may simultaneously benefit communities by reducing crime while also initiating lasting change for American policing by reducing crime committed by police officers.

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APPENDIX A. PACKAGES USED WITH RSTUDIO

Package Name	**Author(s)**	**Purpose**
readxl	Hadley Wickham et al.	Importing data from Excel format
writexl	Jeroen Ooms	Exporting data to Excel format
haven	Hadley Wickham, Evan Miller, Danny Smith	Importing and exporting SPSS and Stata data files
dplyr	Hadley Wickham et al.	Data manipulation
tidyverse	Hadley Wickham	Data manipulation
stringr	Hadley Wickham	Data manipulation

APPENDIX B. CORRELATION MATRIX OF VARIABLES USED IN ANALYSES

#	Variable	1	2	3	4	5	6	7	8	9	10	11
1	Police crime	1.000										
2	General crime (UCR)	0.565	1.000									
3	Crimes against persons (UCR)	0.568	0.987	1.000								
4	Crimes against property (UCR)	0.569	0.988	0.985	1.000							
5	Crimes against society (UCR)	0.551	0.993	0.965	0.964	1.000						
6	Gini index	0.191	0.146	0.150	0.143	0.142	1.000					
7	Percent below poverty line	0.009	-0.088	-0.067	-0.079	-0.099	0.565	1.000				
8	Percent unemployed	0.084	0.087	0.104	0.085	0.081	0.257	0.574	1.000			
9	Percent uninsured	-0.004	-0.063	-0.044	-0.061	-0.070	0.278	0.560	0.352	1.000		
10	Percent female headed households	0.169	0.161	0.175	0.161	0.152	0.350	0.537	0.486	0.340	1.000	
11	Percent owner-occupied housing units	-0.298	-0.302	-0.309	-0.299	-0.295	-0.384	-0.352	-0.197	-0.218	-0.475	1.000
12	Percent vacant housing units	-0.122	-0.241	-0.228	-0.231	-0.247	0.081	0.144	0.073	0.234	-0.221	0.217
13	Percent high school educated	0.022	0.102	0.074	0.095	0.114	-0.340	-0.661	-0.415	-0.601	-0.408	0.097
14	Law enforcement agencies	0.507	0.694	0.652	0.647	0.721	0.151	-0.102	0.051	-0.100	0.141	-0.201
15	Sworn law enforcement officers	0.660	0.565	0.572	0.575	0.548	0.180	-0.028	0.048	-0.021	0.099	-0.289
16	Percent agencies reported (UCR)	-0.030	0.057	0.055	0.053	0.058	-0.078	-0.057	0.082	-0.152	-0.111	0.032
17	Rurality	-0.271	-0.425	-0.409	-0.405	-0.433	0.020	0.190	-0.127	0.184	-0.259	0.209
18	Total population / 10,000	0.683	0.852	0.861	0.862	0.828	0.145	-0.066	0.063	-0.028	0.121	-0.280
19	Sex ratio	-0.099	-0.122	-0.118	-0.120	-0.123	-0.128	-0.029	-0.045	0.103	-0.130	0.033
20	Age-dependency ratio	-0.175	-0.247	-0.243	-0.233	-0.250	-0.125	-0.248	-0.161	-0.237	-0.506	0.545
21	Percent White	-0.232	-0.186	-0.204	-0.190	-0.174	-0.373	-0.449	-0.457	-0.372	-0.671	0.470

#	Variable	12	13	14	15	16	17	18	19	20	21
1	Police crime										
2	General crime (UCR)										
3	Crimes against persons (UCR)										
4	Crimes against property (UCR)										
5	Crimes against society (UCR)										
6	Gini index										
7	Percent below poverty line										
8	Percent unemployed										
9	Percent uninsured										
10	Percent female headed households										
11	Percent owner-occupied housing units										
12	Percent vacant housing units	1.000									
13	Percent high school educated	-0.081	1.000								
14	Law enforcement agencies	-0.228	0.121	1.000							
15	Sworn law enforcement officers	-0.124	0.046	0.526	1.000						
16	Percent agencies reported (UCR)	0.078	0.058	-0.139	-0.044	1.000					
17	Rurality	0.490	-0.164	-0.409	-0.239	-0.001	1.000				
18	Total population / 10,000	-0.186	0.065	0.646	0.774	-0.004	-0.326	1.000			
19	Sex ratio	0.209	-0.096	-0.138	-0.082	-0.001	0.204	-0.091	1.000		
20	Age-dependency ratio	0.464	0.175	-0.182	-0.149	0.137	0.413	-0.197	0.007	1.000	
21	Percent White	0.039	0.308	-0.122	-0.183	0.070	0.173	-0.191	0.011	0.394	1.000

APPENDIX C. MODELS REGRESSING POLICE CRIME ON PREDICTORS

Appendix C. Mixed-Effects Models Regressing Police Crime on Predictors; *n*=3,133 Counties.

	Model 1		Model 2		Model 3	
	b_z	SE	b_z	SE	b_z	SE
Social disorganization variables						
Gini index	.074	.007***	.032	.006***	.026	.005***
Percent owner-occupied housing units	-.118	.007***	-.089	.005***	-.046	.005***
Percent vacant housing units	-.044	.006***	-.006	.005	.021	.005***
Cumulative disadvantage	-.062	.007***	-.020	.005***	-.026	.005***
Demographic characteristics						
Law enforcement agencies	--	--	.203	.005***	.088	.005***
Rurality	--	--	--	--	-.062	.005***
Total population / 10,000	--	--	--	--	.154	.004***
Sex ratio	--	--	--	--	-.015	.005**
Age-dependency ratio	--	--	--	--	.000	.005
Percent White	--	--	--	--	-.038	.005***
Intercept	.172	.006***	.173	.005***	.172	.004***
Model statistics						
Wald χ^2	769.09***		2,829.73***		5,175.06***	
Between cluster variance	0.084		0.084		0.084	
Within cluster variance	0.088		0.052		0.032	

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

APPENDIX D. MODELS REGRESSING GENERAL CRIME ON PREDICTORS

Appendix D. Mixed-Effects Models Regressing General Crime on Predictors; *n*=2,511 Counties.

	Model 1		Model 2		Model 3	
	b_z	SE	b_z	SE	b_z	SE
Social disorganization variables						
Gini index	.188	.033***	.031	.029	-.006	.024
Percent owner-occupied housing units	-.440	.032***	-.334	.028***	-.161	.025***
Percent vacant housing units	-.553	.029***	-.415	.026***	-.092	.023***
Cumulative disadvantage	-.139	.033***	.031	.029	.121	.025***
Demographic characteristics						
Law enforcement agencies	--	--	.733	.025***	.440	.026***
Rurality	--	--	--	--	-.626	.027***
Total population / 10,000	--	--	--	--	.067	.025**
Sex ratio	--	--	--	--	-.245	.025***
Age-dependency ratio	--	--	--	--	-.355	.026***
Percent White	--	--	--	--	-.006	.025
Intercept	6.670	.027***	6.668	.024***	6.671	.019***
Model statistics						
Wald χ^2	887.93***		2,014.98***		4,534.77***	
Between cluster variance	0.088		0.088		0.088	
Within cluster variance	1.862		1.391		0.884	

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

APPENDIX E. CLOGG TEST

Appendix E. Clogg Test for Models Regressing Police Crime and General Crime on Unstandardized Predictors.

	Police Crime		General Crime		Clogg Test
	n=3,133		*n*=2,511		
	b	BSE	b	BSE	Z
Social disorganization variables					
Gini index	.746	.070***	.160	.205	2.705**
Percent owner-occupied housing units	-.006	.000***	-.020	.001***	12.999***
Percent vacant housing units	.002	.000***	-.009	.001***	10.786***
Cumulative disadvantage	-.005	.001***	.026	.002***	-13.864***
Demographic characteristics					
Law enforcement agencies	.012	.001***	.061	.001***	-34.648***
Rurality	-.023	.001***	-.231	.004***	50.447***
Total population / 10,000	.005	.000***	.002	.002**	6.000***
Sex ratio	-.001	.000***	-.020	.001***	18.906***
Age-dependency ratio	-.000	.000	-.035	.001***	34.301***
Percent White	-.002	.000***	-.000	.001	-1.569
Intercept	.616	.053***	12.975	.513***	-76.328***
Model statistics					
Wald χ^2	5,206.66***		52,342.51***		
Between cluster variance	0.084		0.088		
Within cluster variance	0.032		.884		

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

APPENDIX F. MODELS REGRESSING POLICE CRIME ON PREDICTORS

Appendix F. Mixed-Effects Models Regressing Police Crime on Predictors; *n*=2,542 Counties.

	Model 1		Model 2		Model 3	
	b_z	SE	b_z	SE	b_z	SE
Focal independent variables						
Lagged general crime (UCR)	.231	.005***	.209	.005***	.187	.005***
Social disorganization variables						
Gini index	--	--	.039	.006***	.035	.006***
Percent owner-occupied housing units	--	--	-.045	.006***	-.030	.006***
Percent vacant housing units	--	--	-.011	.005*	.014	.006*
Cumulative disadvantage	--	--	-.019	.006***	-.030	.006***
Demographic characteristics						
Rurality	--	--	--	--	-.053	.007***
Sex ratio	--	--	--	--	-.017	.006**
Age-dependency ratio	--	--	--	--	-.003	.006
Percent White	--	--	--	--	-.047	.006***
Intercept	.162	.005***	.162	.005***	.164	.005***
Model statistics						
Wald χ^2	2,514.17***		2,836.18***		3,252.23***	
Between cluster SD	.087		.087		.087	
Within cluster SD	.042		.039		.035	

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

APPENDIX G. MODELS REGRESSING POLICE CRIME ON PREDICTORS

Appendix G. Mixed-Effects Models Regressing Police Crime on Predictors; *n*=2,542 Counties.

	Model 1		Model 2		Model 3	
	b_z	SE	b_z	SE	b_z	SE
Focal independent variables						
Lagged crimes against persons (UCR)	.183	.005***	--	--	--	--
Lagged crimes against property (UCR)	--	--	.178	.005***	--	--
Lagged crimes against society (UCR)	--	--	--	--	.187	.005***
Social disorganization variables						
Gini index	.038	.006***	.037	.006***	.034	.006***
Percent owner-occupied housing units	-.029	.006***	-.032	.006***	-.031	.006***
Percent vacant housing units	.013	.006*	.014	.006*	.015	.006***
Cumulative disadvantage	-.036	.006***	-.032	.006***	-.029	.006***
Demographic characteristics						
Rurality	-.056	.007***	-.060	.007***	-.052	.007***
Sex ratio	-.017	.006**	-.016	.006**	-.017	.006***
Age-dependency ratio	-.006	.006	-.004	.006	-.002	.006
Percent White	-.045	.006***	-.046	.006***	-.049	.006***
Intercept	.164	.005***	.164	.005***	.164	.005***
Model statistics						
Wald χ^2	3,181.83***		3,063.49***		3,225.60***	
Between cluster SD	.087		.087		.087	
Within cluster SD	.035		.037		.035	

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

APPENDIX H. MODELS REGRESSING GENERAL CRIME ON PREDICTORS

Appendix H. Mixed-Effects Models Regressing General Crime on Predictors; *n*=2,511 Counties.

	Model 1		Model 2		Model 3	
	b_z	SE	b_z	SE	b_z	SE
Focal independent variables						
Lagged police crime	.020	.006***	.017	.006**	.001	.006
Social disorganization variables						
Gini index	--	--	.186	.033***	.006	.024
Percent owner-occupied housing units	--	--	-.436	.032***	-.169	.025***
Percent vacant housing units	--	--	-.552	.029***	-.092	.023***
Cumulative disadvantage	--	--	-.137	.033***	.119	.025***
Demographic characteristics						
Law enforcement agencies	--	--	--	--	.477	.022***
Rurality	--	--	--	--	-.631	.027***
Sex ratio	--	--	--	--	-.243	.025***
Age-dependency ratio	--	--	--	--	-.352	.026***
Percent White	--	--	--	--	-.012	.025
Intercept	6.69	.032***	6.67	.027***	6.67	.019***
Model statistics						
Wald χ^2	12.25***		901.18***		4,514.08***	
Between cluster SD	.088		.088		.088	
Within cluster SD	2.509		1.851		.887	

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$